THE EFFECT OF ACHIEVING "MEANINGFUL USE" AMONG MARYLAND MEDICAID MANAGED CARE NETWORK PROVIDERS ON HEDIS CHILDHOOD IMMUNIZATION STATUS SCORES

by

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ABSTRACT

Context Among other things, the American Recovery and Reinvestment Act of 2009 (ARRA) provided financial incentives for certain medical providers to adopt and meaningfully use certified Electronic Health Records (EHR). Health Information Technology (HIT), particularly EHRs, may improve the quality of health care.

Objective To estimate the effect of Electronic Health Records (EHR) implemented by Maryland Medicaid managed care network physicians participating in the Maryland EHR Incentive Program on a Healthcare Effectiveness Data and Information Set (HEDIS®)-like measure for immunization administration.

Design, Setting, and Participants This study used an interrupted time series to estimate the impact of EHR use on the quality of care provided to Maryland Medicaid managed care recipients. Data are analyzed using a hierarchical model. The time period for this study is 2010 through 2014, with the intervention period, calendar year 2013. To be included in the intervention group, a physician must have met HEDIS®-like inclusion criteria and measurement thresholds for Childhood Immunization Status (NQF 0038, Combination 7) and must have met "Meaningful Use" during calendar year 2013 (147 providers); matched comparisons came from Maryland Medicaid Managed Care Organization (MCO) network providers.

Main Outcome Measure The estimated effect of EHR use on HEDIS®-based quality metric, Childhood Immunization Status (CIS) Combination 7, comparing EHR users to non-users pre-and post-implementation of the EHR Incentive Program in Maryland Medicaid.

Results and Implications Based on prior information and the probabilities calculated with this data set for Maryland Medicaid MCO network providers, in the two-year post-EHR implementation period, there is no statistically significant difference in the change in the odds of

meeting CIS Combination 7, comparing providers meeting Meaningful Use with Clinical Quality Measure (eCQM) National Quality Forum 0038 “Childhood Immunization Status,” to non-EHR users.

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Introduction

PROBLEM STATEMENT

As a percent of Gross Domestic Product (GDP) and per capita, the United States spends more on health care than any other industrialized nation; yet, the quality of care received is variable (Squires, 2012). Historically, the United States' growth rate in GDP and per capita health care spending has far outpaced other nations, driven in part by health care technology (Squires 2012, Feldstein, 2007).

Despite the potential correlation between increased health care costs and technology, in 2009 the United States embarked on a major health information technology (HIT) expansion. This expansion arose primarily from research highlighting some of the benefits of HIT. HIT may reduce costs and inefficiencies in health care by electronically linking doctors, insurance providers, pharmacies, and government institutions to consumers and their individual health information. Cost savings may be achieved through reduction in administrative overhead, while inefficiencies mitigated through better monitoring of health care services, particularly duplicative treatments and tests. The quality of health care could be improved by providing on-demand integrated and longitudinal patient information, guideline-based care, and decision support (Zhou et al., 2009). Total cost savings due to HIT could reach $80 billion (Girosi, Federico, Meili, Robin C., Scoville, 2005).

To encourage EHR adoption, the U.S. government invested an estimated $37 billion dollars in incentive payments to providers participating in the Electronic Health Records Incentive Program (*Active Registrations: December 2017 EHR Incentive Program*, 2017). The total investment in the EHR Incentive Program is likely more than $37 billion due to state administrative costs. The EHR Incentive Program provides financial incentives for certain providers and hospitals to adopt and then "meaningfully use" federally-certified EHRs (Thune, John, Alexander, Lamar, Roberts, Pat, Burr, Richard, Coburn, Thomas, Enzi, 2013).

Due in part to the only-recently widespread use of certified EHRs and the difficulty in isolating the impact of EHR use and particular EHR functionality on outcomes, few studies exist to explore the relationship between EHR use and the quality of health care. Absent this information, it is unclear whether EHRs do or will deliver on any of its potential benefits. If EHRs are able to improve the quality of health care, the use of EHRs by Medicaid providers could improve the quality of health care delivered to one of the core recipients of Medicaid services: children in poverty.

STUDY AIMS

The primary aim of this study is to estimate the effect on health care quality of Electronic Health Records (EHR) implemented by certain Maryland Medicaid managed care network providers. This study compares a modified, process-based quality metric specified by the Agency for Healthcare Research and Quality's (AHRQ) Healthcare Effectiveness Data Information Set (HEDIS®) that aligns closely with the quality measure specified in the EHR Incentive Program. The HEDIS® quality metric is the Childhood Immunization Status (CIS) measured as the percent of children 2 years of age who received the appropriate immunizations.

HEDIS® specifies up to ten combinations of vaccinations with the following frequencies: The percent of children who by their second birthday had four diphtheria, tetanus and acellular pertussis (DTaP); three polio (IPV); one measles, mumps and rubella (MMR); two H influenza type B (HiB); three hepatitis B (HepB), one chicken pox (VZV); four pneumococcal conjugate (PCV); two hepatitis A (HepA); two or three rotavirus (RV); and two influenza (flu) vaccines. Although influenza is included in the HEDIS® CIS measure, I excluded this vaccination in this analysis because its delivery is seasonal. Additionally, I considered a Medicaid recipient up-to-date with their HepB vaccination if they received at least two of three required doses because this study focuses on physicians who act as a Medicaid recipient's Primary Care Provider (PCP), and the HepB vaccine can be administered at birth.

Additional aims of this study include:

- Investigating whether quality differs by EHR developer, and
- Discussing the implications of EHR use on physician quality reporting and pay-for-outcomes policies.

Maryland launched the Medicaid EHR Incentive Program in 2011, making its first incentive payment in December of that year. The EHR Incentive Program pays providers a financial incentive for first adopting and then in later years "meaningfully using" their EHR. During the timeframe of this study, the Centers for Medicare and Medicaid Services (CMS) defined "meaningful use" through rulemaking via a list of "core" and "menu set" objectives and electronic Clinical Quality Measures (eCQM). Recent rulemaking has abolished the "core" and "menu" set paradigm, but has preserved eCQMs, including the immunization measure used in this study (U.S. Department of Health & Human Services, 2015). Ostensibly, providers who

achieve “meaningful use” have optimized their EHRs, increasing the probability of improved quality and reduced cost.

Currently, Maryland evaluates the quality of health care delivered by Managed Care Organizations (MCOs) using HEDIS®. HEDIS® contains a series of standardized process-based quality measures from which Maryland Medicaid chooses select items to compare MCOs and to drive the State’s pay-for-performance program, Value Based Purchasing (VBP).

SIGNIFICANCE

As health care practitioners move from adopting EHRs to implementing them into their workflow, it is important to assess whether their acquisition is reducing cost and improving quality, and, if so, in what situations.

Between 2009 and 2013, the Federal government paid out almost $7 billion dollars in incentives to over 147,000 providers (Centers for Medicare and Medicaid Services, 2014b). In 2011, across all health care providers in the United States, an estimated 54 percent had adopted an EHR (E. Jamoom et al., 2012).

In 2010, an estimated 23.7 percent of providers nationally had adopted an EHR, which mirrored the adoption rate among the Maryland Medicaid provider population (Maryland Department of Health and Mental Hygiene, 2014). In 2013, the estimated EHR adoption rate among the Medicaid provider population had grown to nearly 50 percent (Maryland Department of Health and Mental Hygiene, 2014). By 2017, the Maryland Department of Health estimated adoption rate among Medicaid provider population to be 74 percent (Maryland Department of Health, 2017). Between 2011 and 2014, Maryland paid over 2,278 providers a total of more than $127 million (Maryland Department of Health, 2017).

As enrollment in the EHR Incentive Program continues to grow, Medicaid agencies will have new options for measuring quality, such as using quality data to better understand the relationship between an individual provider or their care team's contribution to patient outcomes. Before the EHR Incentive Program, the relatively low use of EHRs and the non-standard nature of EHR products made calculating and tracking outcomes across providers difficult. Within Medicaid agencies, HEDIS® is the primary method of tracking quality. HEDIS® generally uses administrative data with occasionally hybrid methodologies for medical record data supplements to calculate their process-based quality measures.

HEDIS® managed care measures pool data across managed care plans and do not assess individual providers. With standardized EHR systems, Medicaid agencies will soon be able to collect patient-level data by provider to compare like providers to like providers longitudinally, allowing for pay-for-outcomes models. However, until the adoption of certified EHRs is widespread, any longitudinal analysis of quality must rely on HEDIS®-like quality methodologies.

Some process-based measures have an outcome focus; for example, immunization status is linked to reductions in mortality. Using a systematic review and analysis of national data and applying it to a hypothetical birth cohort of 4 million US-Census based individuals, Maciosek et al., (2006), estimated that administering vaccinations in accordance with national childhood immunization schedules is a highly cost-effective intervention that could result in saving greater than 360,000 quality-adjusted life years (QALY) (2006). Although vaccination schedules vary worldwide and few studies exist that measure the association between immunization schedules, health outcomes, and adverse events, vaccines have contributed significantly to reductions in morbidity and mortality (Institute of Medicine, 2013).

Despite the importance of vaccination for reducing morbidity and mortality, the immunization rate in the United States remains below national targets. In 2013, 70.4 percent of children ages 19-35 months received the full Center for Disease Control and Prevention (CDC) recommended vaccine series (Elam-Evans, Laurie D, Yankey, David, Singleton, James A., Kolasa, 2014). For Medicaid children up through age 2 in 2014, the national mean immunization rate was 62.1 percent (Burwell, 2016).[1]

[1] The immunization rate is reported using Combination 3, which includes vaccination administration for DTAP, IPV, MMR, HIB, HEPB, VZV, and PCV.

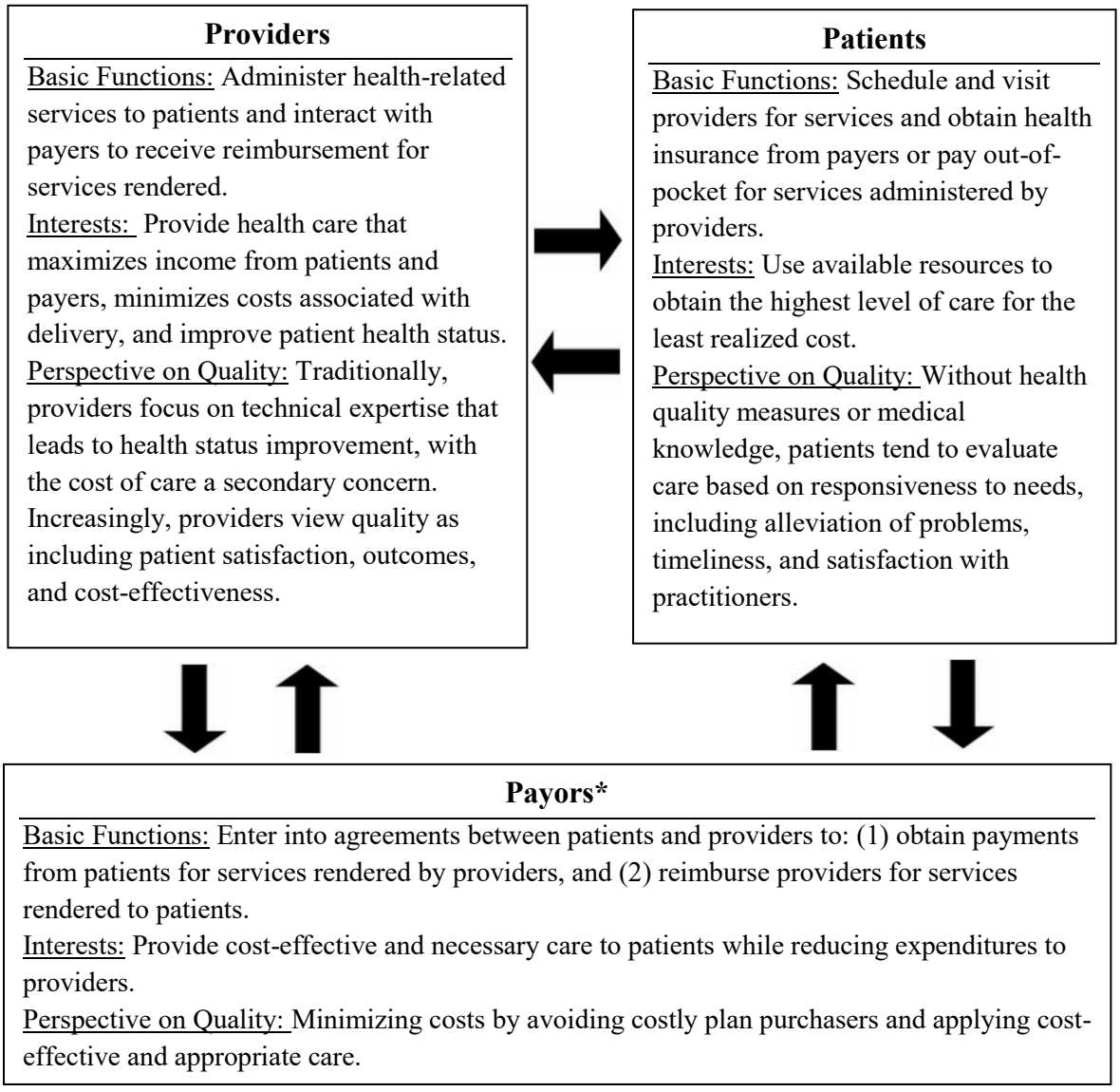
Chapter 2
Literature Review

Defining Health Care Quality

Historically, approaches to measuring the quality of health care followed Donabedian's structure, process, and outcomes framework (1966). "Structure" includes the conditions under which care is provided; "process" includes how care is delivered; and "outcomes" are the results of care (Donabedian, 1966). According to Rubin, Provonost, and Diette, process measures are appealing quality assessment tools because they can be actionable, avoid the need for patient-level risk adjustment, and have the potential to link to outcomes (Rubin, Pronovost, & Diette, 2001). Since they are ultimately the result of a health-care intervention, outcomes-based measures may be more preferable to process-based measures; however, the complexity and expense of developing and standardizing these measures has reduced their widespread use (Rubin et al., 2001).

Identifying quality measures for the U.S. health care market using Donabedian's framework is difficult. Part of the difficulty in identifying quality measures is that each of the various stakeholders who participate in the traditional U.S. health care system has a unique perspective on health care. Figure 1 provides a simplified diagram for viewing the interactions among the three major health care stakeholders (providers, payors, and patients), taking into account their basic functions, interests and motivations in the health care market, and perspectives on quality (Allison, 1969; Brinkerhoff, Derick W., Crosby, 2002; McGlynn, 1997).

Achieving convergence on an approach to measuring quality requires balancing these competing expectations (McGlynn, 1997).



* The term "payors" refers to any entity paying some or all of a provider's bill on behalf of the patient. This includes, but is not limited to, employers, traditional health insurers, and managed care organizations.

Figure 1 : Group Interaction Diagram for the American Health Care Market

Preventative services are a good example of where provider, patient, and payer expectations for quality may intersect. Preventative services, such as childhood vaccinations, meet the quality expectations of patients and payers in that they are both effective at reducing mortality and morbidity and cost-effective (Maciosek et al., 2006). In addition to their effectiveness in reducing mortality and morbidity, childhood vaccinations may also appeal to provider expectations of quality in that they are easy to administer and require relatively minimal effort to achieve compliance, particularly with the aid of IT systems (McGlynn, 1997).

Further, childhood vaccines are often available for free through the federal Vaccines for Children (VFC) program, and, among the Maryland Medicaid population, vaccine administration is reimbursed at the same rate, regardless of the vaccine. These financial factors may make it more likely that if a provider provides any childhood vaccines to Medicaid recipients, the provider may provide them all.

Even though childhood vaccinations may provide a good service for defining health care quality, determining how to measure the administration of childhood vaccinations is challenging. Based on such factors as the type of vaccine, recipient age, and recipient's immune status, the timing and dose of the vaccine matters (Kroger, Sumaya, Pickering, & Atkinson, 2011). These factors combine to determine the optimal effectiveness of the vaccine to elicit a protective immunoresponse. To help ensure the timely administration of the appropriate dosage of vaccines to be administered to persons aged 0-18 years, the Advisory Committee for Immunization Practices for the CDC annually publishes a recommended vaccine schedule.[2]

Despite the importance of the timing and dose of the vaccine, timeliness and over-immunization (excessive dose) are not fully factored into traditional process-based

[2] For the 2015 immunization schedule, see http://www.cdc.gov/vaccines/schedules/easy-to-read/child.html.

measurements of immunization quality. The National Committee for Quality Assurance (NCAQ) relies on process-based measures to develop their HEDIS® program. Over 90 percent of health care plans, particularly Medicaid Managed Care plans, use HEDIS® scoring to measure quality (Bundy, Solomon, Kim, & Miller, 2012). One of the HEDIS® measures is childhood immunization status score. HEDIS® measures immunization status by looking at the number of children by age 2 that receive the recommended doses of vaccines as administered by the health care plan's network providers.

Glauber (2003) notes that NCAQ's approach to measuring immunization status does not adequately address childhood immunization statuses because:

1. By combining all immunizations that should be delivered by age 2, HEDIS® will consider a child not up-to-date whether they miss one or all recommended immunizations.
2. The determination of the status of "up-to-date" depends on obtaining all recommended doses of any one vaccine, even if obtaining later doses are the least biologically relevant doses.
3. Measuring up-to-date status based at age 2 fails to take into account the timeliness of each vaccination.

Further, HEDIS® only looks at within-health-plan immunization administration. It does not take into account whether a recipient received an immunization from an out-of-network provider. The implications of not factoring in out-of-network vaccination administration may lead to extra-immunization, which is an inefficient use of resources and potentially harmful to patients (Feikema, 2000). The differential impact of Medicaid insurance status compared to commercial insurance status on extra-immunization is unknown.

Thus, quality analysis of immunization status may need to rely on the HEDIS®-based approach to provide for benchmarking but should not solely rely on HEDIS®. Instead, quality reporting of immunization status should supplement HEDIS® by making a clinically relevant measurement of timeliness and leverage data from vaccine registries or other health care system wide data to reduce extra-immunization.

THEORETICAL BASIS FOR QUALITY IMPROVEMENT

Generally, EHR systems show evidence of quality improvement when it comes to aiding in protocol or guideline-based care (Chaundhry et al., 2006). Using EHRs to guide care may prevent costly medical errors, such as adverse drug events, or unnecessary health services. Some studies cite the potential reduction in medical errors from HIT between 50 and over 90 percent (Congressional Budget Office, 2008). A 2014 systematic review of 28 randomized control trials implementing rule- or algorithm-based Clinical Decision Support (CDS) integrated with an EHR found marginal positive impacts on morbidity and no effect on mortality (Moja et al., 2014). And while the use of HIT, particularly CDS, may reduce medical errors and provide guidance on protocol, research does not support the assumption that improved care necessarily improves patients' health or reduces costs (Congressional Budget Office, 2008). As applied to vaccine-based interventions, CDS impacts on vaccination rates varies (Sittig, Teich, Osheroff, & Singh, 2009; Stockwell & Fiks, 2013).

However, before the creation of the EHR Incentive Program in 2009, few hospitals and health care providers had adopted an EHR, and those that did adopt these systems customized them to meet particular health-care needs (Congressional Budget Office, 2008). Using a national survey, Jha et al. estimated that 24 percent of office-based physicians had an EHR in 2006 (Jha

et al., 2006). A 2007 survey by the American Hospital Association estimated EHR an 11 percent EHR adoption rate by non-federal hospitals (Congressional Budget Office, 2008). Because of the proliferation of customized EHRs, nearly any evidence correlating the use of EHRs with quality improvement could not easily be generalized. To better standardize and ensure the availability of quality-impacting EHR functionality and to guarantee that health care providers or hospitals participating in the Medicare or Medicaid EHR Incentive Programs have access to the technology necessary to meet Incentive Program requirements, the federal government created national standards and certification requirements for EHRs. By creating a national EHR certification program, the federal government increased the probability that providers adopting EHRs would implement those EHR functionalities with the strongest link to improving health care quality.

CERTIFIED ELECTRONIC HEALTH RECORD TECHNOLOGY (CEHRT)

Periodically, the Department of Health and Human Services' Office of the National Coordinator (ONC) promulgates rules for EHRs to receive federal certification. ONC generally promulgates Certified Electronic Health Record Technology (CEHRT) rules to coincide with the various stages of Meaningful Use. In anticipation of providers and hospitals preparing for Meaningful Use Stage 1, ONC published the requirements for 2011 Edition CEHRT in July of 2010 (HHS, 2010). For Program Year 2013, all providers and hospitals participating in the Medicare or Medicaid EHR Incentive Program must have EHR technology certified to the 2011 CEHRT edition. Due to flexibility afforded to Medicare and Medicaid Incentive Program participants in Program Year 2014 by HHS, all EHR Incentive Program participants could use

2011 CEHRT to meet Meaningful Use until Program Year 2015 (U.S. Department of Health & Human Services, 2013).

In regards to the Meaningful Use Stage 1 public health measure, "capability to submit electronic data to immunization registries … and actual submission in accordance with applicable laws and practice," an EHR certified to the 2011 Edition of CEHRT must have been able to "electronically record, modify, retrieve, and submit immunization information in accordance with" Health Level 7 (HL7) version 2.3.1 and 2.5.1 (HHS, 2010).

However, obtaining 2011 Edition CEHRT did not guarantee that a health care provider could export and transport a message acceptable to any State's Immunization Information System (IIS). In many cases, each State or jurisdiction uses the HL7 Implementation Guide as a starting point, adding other nuances or required fields within the message. Additionally, in response to a Congressional request to report on the pervasiveness of health information blocking, the ONC reported that some EHR vendors charge providers to send, receive, or export health information (Office of the National Coordinator, 2015). Since public health reporting requires the sending or exporting of health information, it is likely that meeting any public health measure may be difficult for some providers with CEHRT.

Additionally, a health care provider who obtained a 2011 Edition CEHRT would not necessarily know whether or not their product could be configured to trigger a Clinical Decision Support (CDS) rule for vaccinations. According to 2011 Edition CEHRT requirements, CDS must have been available for real-time notifications and care suggestions based on data elements from "medication lists; demographics; and laboratory test results" (HHS, 2010). Thus, the certification requirement ensures the capability is present within any 2011 Edition CEHRT, but what flavors of CDS are implemented depend upon the EHR vendor, the level of customization

present in the EHR product, and the willingness of the EHR purchaser to code and invoke a specific CDS. Because 2011 Edition CEHRT stopped short of prescribing the exact types of CDS available, there is no way from a CEHRT Identification Number to determine whether a particular product offers or if a purchaser of a particular product enables a vaccine-based CDS rule.

In 2011, the CDC convened an expert panel to assist with determining rules around Clinical Decision Support for Immunizations (CDSi) (Artz, 2016). As described by Artz, CDSi could vary in sophistication, from web-based standard transactions with an IIS or simple demographic-based rules to remind health care providers for the need to administer vaccinations (2016).

EHR Adoption Challenges

Despite the potential gains for EHR adopters, financial, technical, and time barriers may hinder the widespread adoption of EHRs. A systematic literature review of health care providers' barriers to EHR adoption by Boonstra and Broekhuis (2010) identified these categories as the most frequently cited among the literature. These barriers to EHR adoption are often cited by Maryland Medicaid providers as well (Maryland Department of Health and Mental Hygiene, 2014).

Financial barriers include high start-up and on-going maintenance and support costs (Boonstra & Broekhuis, 2010). Technical barriers include difficulties in selection, integrating, and operating a new system (Boonstra & Broekhuis, 2010). Time barriers are related to the technical barriers in that they span the EHR life cycle, from time spent on researching and

selecting a system, to training on the system, and finally working on the system instead of conversing with patients (Boonstra & Broekhuis, 2010).

In looking at a 2011 nationally representative sample of non-federal office-based providers EHR adopters compared to non-adopters, Jamoom et al. found that, while the cost of purchasing remained the number one barrier for EHR adopters (52%) and non-adopters (73%), both adopters and non-adopters ranked the perception of productivity loss as the second greatest barrier (37% versus 59%, respectively) (E. W. Jamoom, Patel, Furukawa, & King, 2014).

CHALLENGES FOR QUALITY IMPROVEMENT

Although EHR systems leverage a logical and standardized data structure to record and extract clinical data, simply possessing an EHR does not necessarily equate to more reliable and valid quality reporting. Further, a nation-wide change from International Classification of Disease (ICD) version 9 to ICD-10 coding on October 1, 2015 will likely impact longitudinal comparison of guideline-based quality reporting.

A review of empirical studies conducted by Chan, Fowles, and Weiner concluded that the reliability of quality reporting varied by EHR functional modules (e.g., problem and medication lists), data documentation and extraction strongly influenced quality outcomes, and the use of and extraction process for free-text fields may prove problematic for quality reporting (Chan, Fowles, & Weiner, 2010).

However, because EHRs can be used to record information as structured data at the point of care, the data recorded as clinical data may be more complete and reliable than administrative data, the traditional method for quality evaluation. Some quality-based measures calculate the percent of eligible patients receiving some level of guideline-based care (process measure), such

as patients with heart disease or diabetes (Rubin et al., 2001). The identification of these disease states is generally coded using ICD-9. In these situations, identifying the target population (denominator) is critical. When comparing the target population for diabetes care using paper medical records abstractions versus EHR data queries, Tang et al. found a 22 percentage point increase in identified individuals (Tang, Paul C. Md, Ms, Mary Ralston, Phd, Michelle Fernandez Arrigotti & Lubna Qureshi, Ms, Justin Graham, Md, 2007). The researchers did not comment on the correctness of either extraction approach, but instead highlighted the discrepancies in quality reporting resulting from either approach.

While inconsistencies exist in quality measurements between claims-based and EHR-based reporting, this inconsistency may become problematic when the language used to classify diseases changes from ICD-9 to ICD-10. On January 16, 2009, the Department of Health and Human Services (HHS) published a final rule mandating the use of ICD-10 codes[3]. This mandate went into effect on October 1, 2015.

The ICD-10 code set is significantly different than ICD-9, allowing for more diagnostic specificity, among other things (American Medical Assocation, 2014). Studies evaluating health care quality using HEDIS®-type measures that span the ICD-10 implementation date should choose measures whose methodologies either do not rely on diagnoses or whose ICD-9-to-10 mappings are equivalent (Centers for Medicare and Medicaid Services, 2014a).

EFFECT OF EHRS ON QUALITY

Studies on the effect of EHR use on quality are mixed and tend to be performed before the implementation of the EHR Incentive Program and federally certified EHR systems. Of the

[3] http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Data-and-Systems/ICD-Coding/ICD-10-Final-Regulation-and-Training.html

studies showing improvements in quality, most do so in relation to specific EHR functionalities or regarding guideline-based quality metrics.

Using a mail survey and historical HEDIS® State-based data, Poon et al. found statistically significant differences in quality scores for certain quality measures based on specific EHR functions (Poon et al., 2010). The authors found positive correlations between EHR functionalities of problem lists, visit notes, and radiology test results and quality measurements for women's health, cancer screening, and cancer prevention (Poon et al., 2010).

Using a matched mailed survey data to State-based HEDIS® data, Zhou et al. found no statistically significant association between EHR use and the quality reporting for six different HEDIS® measure (2009). Theorizing that the duration of EHR use may increase the likelihood of higher quality scores, the authors applied longitudinal data, measuring the average HEDIS® score across EHR users over time. Regression analysis showed no statistically significant association between quality performance and duration of EHR use (Zhou et al., 2009).

Perhaps the most directly applicable source of quality improvement available to an EHR is clinical decision support (CDS). CDS varies in scope, but generally provides clinical reminders to care givers about specific treatment recommendations, but may also be more complex, linking problem lists as well as invoking practice guidelines (Ohno-Machado, 2011). In a systematic literature review, Chaudhry et al. noted that health information technology in general might best improve quality through its adherence to guideline-based care (Chaundhry et al., 2006). Shojania et al. performed a systematic literature review of studies whose intervention involved on-screen computer reminders delivered at the point of care, used randomized or quasi-randomized study design, and had at least one clinical or clinical adherence-based outcome (process-based quality metric) (2009). Based on the 28 studies identified, the authors found a

median improvement of 4.2 percent across all process-based quality metrics, and a 3.8 percent median improvement for vaccinations (Shojania et al., 2009).

Welch et al. noted only a slight positive impact on quality comparing physicians who did not use an EHR with those that had, but these gains only appeared for hypertension and hyperlipidemia (Welch, Pete W., Bazarko, Dawn, Ritten, Kimberly, Burgess, Yo, Harmon, Robert, Sandy, 2007). However, the authors only analyzed information on four practices, with each having varying levels of decision support. In a larger study using a nationally representative sample of ambulatory care visit data between 2005 and 2007, Romano and Stafford did not find a consistent improvement in quality scores comparing EHR users with decision support to non-users (Romano & Stafford, 2011). The authors hypothesized that decision support would lend itself to quality improvement among certain conditions with clear guidelines. Poon et al. used a cross-sectional study design of survey data and found no significant difference in the majority of quality indicators for EHR users versus non-users (2010). Although the authors found higher quality scores for EHR users in two areas, they found decreased quality scores in another.

The literature relating quality to EHR use suggests that quality improvement may have a greater probability of occurring if the EHR functionality links closely with the quality metric and if providers effectively use the functionality. Using a retrospective cross-sectional study of 65 providers eligible for the EHR Incentive Program and practicing within an outpatient network of Federally Qualified Health Centers (FQHC) in New York, Ancker et al. found that those providers who used the functionalities of best-practice alerts, order sets, and panel-level reporting, received statistically significantly higher "meaningful use" quality scores related to the EHR functionality (2015). The "best practice alerts" identified by Ancker et al. are essentially

CDS for the preventative services of tobacco cessation, breast cancer screening, colorectal cancer screening, pneumonia vaccination, and body mass index screening (Ancker et al., 2015).

Although decision support may be the most likely function of an EHR to elicit an improvement in quality, the application of decision support to clinical practice is dependent upon the availability of clear clinical guidelines. Clear clinical guidelines are available for diseases such as asthma, diabetes, and vaccinations. And, based on randomized control trials, researchers showed improvements in adherence to many care guidelines (Bell et al., 2010; Trial, Gilmer, & O'Connor, 2011).

Childhood immunization schedules are an example of guideline-based care that can be facilitated by HIT functionality such as parental reminders and CDS. Parental reminders and CDS use the vaccine schedule and information about the patient to trigger an action by either the patient (parental reminders) or the provider (CDS).

Before the availability of HIT, providers and public health advocates relied on reminder/recall interventions such as telephone or mail, and later text messaging and email to improve patient follow up for care (Stockwell & Fiks, 2013). In the area of vaccinations, this outreach is used to remind patients of an upcoming or missed vaccination. Szilagyi et al. found that missed opportunities for vaccinations are a leading cause of under-vaccination in preschool children, particularly those on Medicaid (P G Szilagyi et al., 1993).

Increasingly, EHR vendors offer text messaging and emailing as a means to engage patients. A systematic review of text messaging as an intervention for pediatric care found significant effects in 71% of studies, particularly for vaccine-based interventions (Militello, Kelly, & Melnyk, 2012). Text-message interventions may be particularly influential in low-income populations, who respond positively to the option of receiving text messages from their

providers when surveyed (Stockwell & Fiks, 2013). Unlike text messaging, email reminders provide less-definitive results, due in part to the low number of studies investigating their impact (Stockwell & Fiks, 2013).

Unlike reminder/recall interventions, EHR CDS focuses on prompting the provider to take some type of action on particular patients, usually during or immediately surrounding the patient encounter. CDS may be effective as a childhood vaccine intervention because it takes advantage of the presence of the child during well- and sick-child visits to reduce the likelihood of missed opportunities to administer or catch up on vaccines. The Advisory Committee for Immunization Practices for the CDC's vaccine schedule lays out when vaccines should be administered and the time period to receive "catch up" vaccinations if necessary. From 0-18 months, a child should receive about 10 vaccinations, depending on dose or combination; and, depending on what dose is scheduled, missing a single opportunity to immunize could reduce the effectiveness of previous doses of a vaccination or prevent immunization from other viruses. Using a historical medical records review of children throughout the United States, Fu et al. found that patients who had any missed opportunity for a vaccination were 3.5 times more likely to be under-immunized compared to those who had no missed opportunities (Fu et al., 2015).

Further, because the age of the child and their immunization status determine their place on the immunization schedule, some missed opportunities to immunize are more significant than others. By reviewing the 2006-2007 National Immunization Survey, Luman and Chu found that about 20 percent of children fell behind their scheduled vaccinations between months 7 and 16, mostly due to the vaccine schedule's requirement for simultaneous vaccination during this interval (Luman & Chu, 2009).

Vaccine-based CDS interventions may improve vaccine rates, but intervening factors such as the implementation of CDS within provider work flow and alert fatigue may dampen CDS's impact on vaccination rates. For vaccine-based CDS, EHRs tend to provide alerts at the point of care, notifying the provider that a patient is due for a particular vaccine (Stockwell & Fiks, 2013). Based on a systematic review of on-screen, point-of-care implementation of vaccine-based CDS in diverse practices seeing adults and children, Stockwell and Fiks found a 4 percent increase in the ordering of recommended vaccines (2013).

However, Sittig et al. (2009) and Osheroff et al. (2007) note that while CDS may be a way to increase the vaccination rate, implementation of CDS in accord with the provider's workflow is important for improving effectiveness (Osheroff et al., 2007; Sittig et al., 2009) . If not implemented appropriately or combined with too many alerts, an alert-based CDS may not be effective (Peter G. Szilagyi et al., 2015). For example, within a single hospital-based network, Fiks et al. showed an increase in HPV vaccine rates from a prompt-based CDS practice compared to a control (2013). Further, in a one-year study across a primary care network implementing CDS alerts with direct access to immunization order sets for well- and sick-child visits for all children under 24 months compared to historical controls, Fiks et al., found statistically significant increases in immunization opportunities and immunization rates (Fiks, Grundmeier, Biggs, Localio, & Alessandrini, 2007). In a separate setting, Szilagyi et al. found no improvement in vaccine rates for adolescents in 24 New York primary care practices comparing EHR-based CDS prompts to no prompts (2015).

Approaches to Studying the Effects of EHR Use on Quality

Studies evaluating the effectiveness of EHRs either take a cross-sectional or longitudinal approach using a pre-post design. Major independent variables include physician characteristics such as age, gender, degree, specialty (primary care provider versus specialty care), country, practice size, and adoption of practice management system (Kern, Barrón, Dhopeshwarkar, Edwards, & Kaushal, 2013; Keyhani et al., 2008). Additional independent variables such as patient panel size per physician and case mix of patients are also used (Kern et al., 2013). Case mix can be estimated using patient-level diagnosis obtained from administrative sources maintained by health plan insurers.

Researchers generally use a dichotomous variable for the presence (or absence) of an EHR as the active independent variable. Researchers tended to operationalize EHR use in this way because of the difficulty of generalizing EHR products within study participants and to the general population as a whole. Prior to the HITECH Act, EHRs tended to be "home-grown": designed with practice-specific functions. Because practices created EHR products to meet their own needs, most studies attempting to measure the impact of EHR use on quality could not create similar groups of EHR (the intervention group), and therefore isolate particular qualities of EHRs with which to correlate an outcome, such as quality. With the increased standardization of EHR products under the HITECH Act and its creation of EHR certification bodies (45 CFR Part 170), it may be easier for researchers to distinguish EHR types and to correlate and generalize EHR use with quality.

Although certification bodies improved the likelihood that all EHRs would contain similar functionalities, such as electronic prescribing (e-Prescribing) or clinical decision support (CDS), these functionalities may be designed differently or integrated into the practice in

different ways, or not at all. Some EHRs come as modules – interconnected functional components or features obtained from different vendors – or as complete systems ("monolithic") by the same vendor. Further, the hardware for either monolithic or modular systems can be housed locally or remotely. A practice's decision to select one of these four types of EHRs may have an impact on practice workflow (*see* Fleming et al., 2014), which, in turn, may have an impact on health care quality.

Researchers focusing on the effect of EHR on quality often use a standardized quality metric as the dependent variable, such as the National Committee for Quality Assurance's (NCQA) Healthcare Effectiveness Data and Information Set (HEDIS®). HEDIS® offers 75 standardize process and quality metrics across eight domains to compare health care plans. These metrics often calculate the percent of eligible patients for a given domain receiving best-practices care.

Two approaches to using HEDIS® measures as an outcome variable include focusing on a handful of provider-specific measures, such as adherence to best-practices guidelines, to measure the proportion of patients who receive that care who were eligible for it or using standard deviations away from the national norm for any relevant measure.

Chapter 3
Methods

This chapter begins with a discussion of my hypothesis and the conceptual framework which informs the hypothesis. Next, I discuss the study design and the causal model. I then provide an overview of the data, particularly data collection and integration. With the data as a backdrop, I then discuss the study population and sample selection process, the data cleaning process, the results of propensity score matching (PSM) used to create the control group, and finally a walkthrough of my model specification.

HYPOTHESES

According to Donabedian, health care quality can be evaluated based on three interconnected areas: structure (the system), process (the activities), and outcomes (the results) (1966). Health care providers adopting an EHR system will likely face a change in their workflow; and this change may impact process, and by extension, quality.

The literature around the impact of EHR implementation on productivity is mixed. Studies show a perceived negative impact on productivity from health care providers, potential improvements to productivity, and decreases in productivity for a limited period of time, followed by increases after an initial 'ramp up' period (Cheriff, Kapur, Qiu, & Cole, 2010). Further, health care provider staff buy-in and technical capability may play a distinctive role in the successful implementation of an EHR (Geibert, 2006).

Based on the above, I hypothesize that **following the intervention, a provider who adopts an EHR will have an increase in their quality score.** Because health care providers may experience various issues related to fully utilizing their EHR during the "ramp-up" period which will be difficult to capture in the analysis, this research creates an aggregated immunization status score for the two years of post-implementation data I obtained.

CONCEPTUAL FRAMEWORK

As the technical components of the health care system have become more complex, Sittig and Singh argue that it is increasingly more difficult to identify a conceptual model to study Health IT interventions (Sittig & Singh, 2010). The authors argue that studies evaluating the effectiveness of Health IT interventions fail to capture how the system and its features interact with both the individuals who use the system and the context in which the system is both acquired and used. In their conceptual model, eight sociotechnical domains are used to evaluate the effectiveness of HIT systems: (1) Hardware and software computing infrastructure; (2) clinical content; (3) human-computer interface; (4) people; (5) workflow and communication; (6) internal organizational policies, procedures, and culture; (7) external rules, regulations, and pressures; and (8) systems measurement and monitoring (Sittig & Singh, 2010).

A systematic literature review by Sockolow et al., took a health services research approach to HIT evaluation (Sockolow, Bowles, Lehmann, Abbott, & Weiner, 2012). The authors' review built upon Ammenwerth and deKeizer's framework and resulted in a HIT Reference-based Evaluation Framework (HITREF) with six dimensions of HIT comprised of various evaluation components. Figure 2 depicts the six dimensions ((1) Structural Quality; (2) Quality of Information Logistics; (3) Unintended Consequences/Benefits; (4) Effects on

Outcome Quality of Care; (5) Effects on Quality Processes; and (6) Barriers or Facilitators to Adoption) and its evaluation components. The model, thus, is a health-services variant of the Technology Acceptance Model (Davis, 1989).

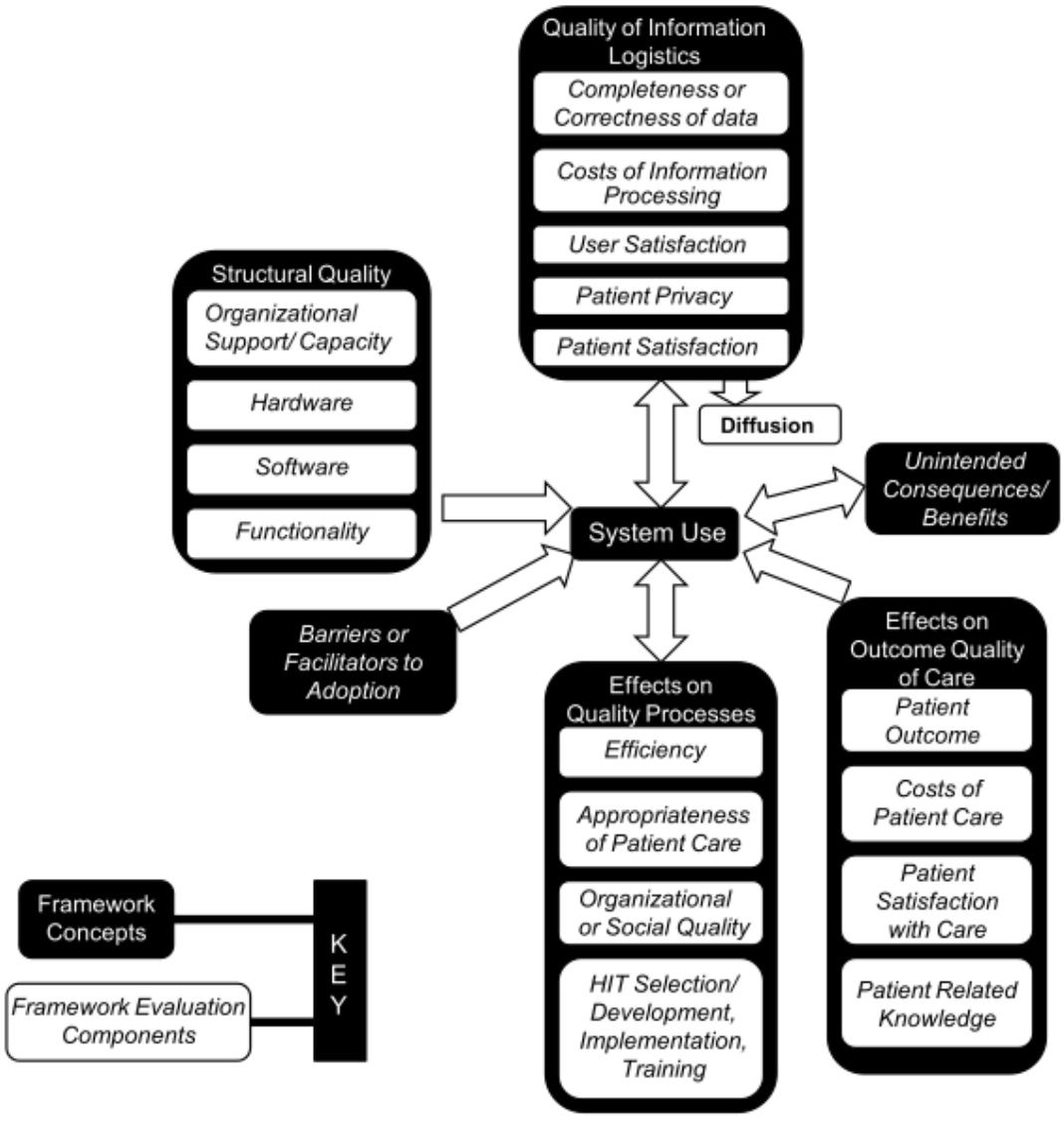


Figure 2: HIT Reference-based Evaluation Framework (HITREF)

This framework is preferable to Sittig and Singh in that it broadens the contextual relationship between the HIT system and its stakeholders (Sockolow, Bowles, Lehmann, Abbott, & Weiner, 2012). Each of the six dimensions feed into user satisfaction with the HIT system, and each of the six dimensions have particular multi-dimensional evaluation components.

As a tool for guiding research into the effects of EHR on quality, the HITREF highlights the importance of contextual factors, such as the type of EHR system used and its usability by practitioners (dimensions Structural Quality and Quality of Information Logistics), as well as the implementation of that system within the general practitioner workflow (Effects on Outcome Quality of Care; Effects on Quality Processes). Further, the characteristics of the providers and patients making up the implementing practice will also influence the satisfaction and use of the system.

To inform my research, I conceptualize the source and target models depicted in Figure 3. The overall theory is that EHR use leads to increases in quality. According to this model, "Meaningful Use" is a proxy for "Electronic Health Records Use" and the Childhood Immunization Status HEDIS® Score is a proxy for "Increased Health Care Quality."

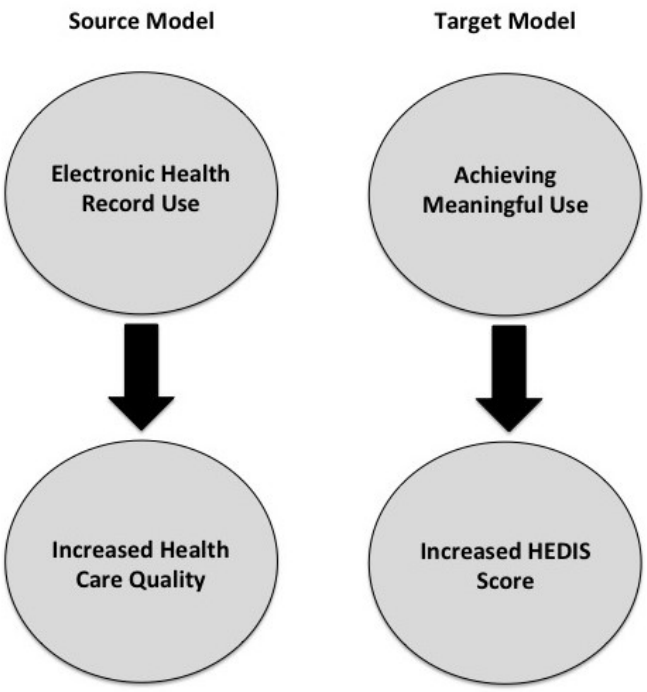


Figure 3: EHR Impact on Quality Conceptualized Source and Target Model

STUDY DESIGN

To understand the association between EHR use and the quality of health care delivered, this research uses an interrupted time series (ITS). An interrupted time series is a quasi-experimental research design with a pre- and post-intervention period, where the intervention can be a policy or program implemented to change an outcome (Penfold & Zhang, 2013). Figure 4 depicts the ITS for this research. Solid boxes represent measurement periods for either HEDIS® scores or "Meaningful Use" for either the intervention or comparison group. The first observation begins in 2010, a full year before Maryland began the Medicaid EHR Incentive Program. Providers selected as the intervention group adopted their EHR in either 2011 or 2012 but achieved meaningful use in 2013.

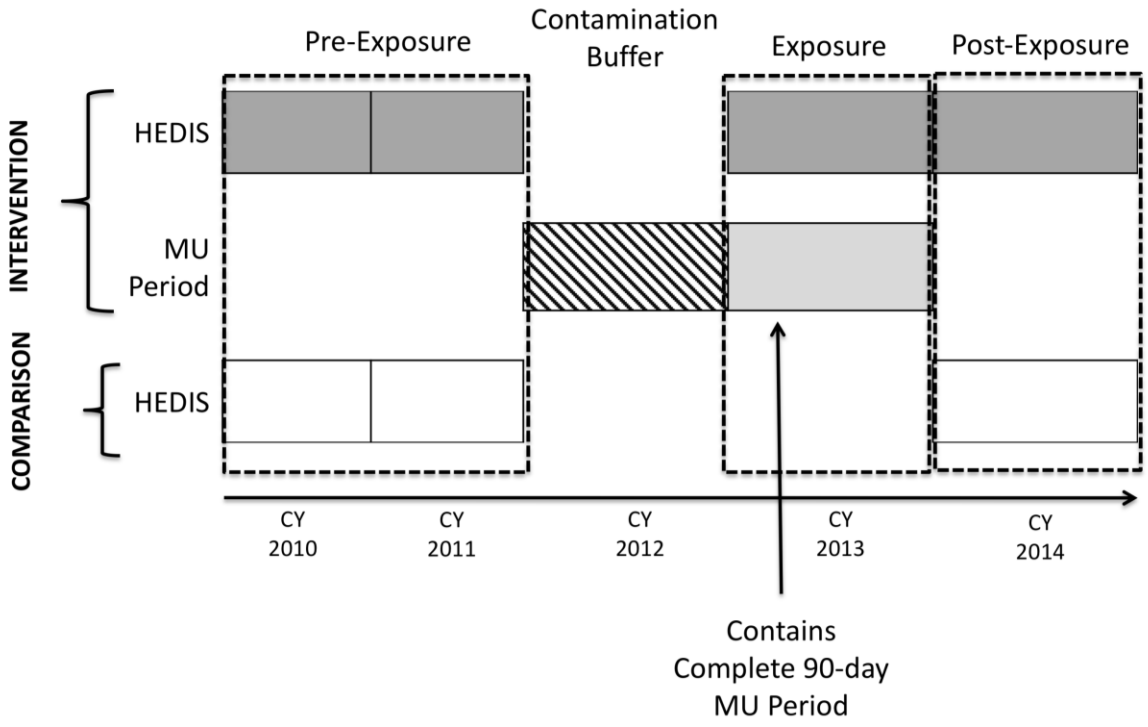


Figure 4: Research Design for Studying the Effect of EHRs on Quality

The outcome measure – immunization status score – is measured by combining the individual-level status score for both 2013 and 2014, the "exposure" and "post-exposure" periods, respectively. To account for prior experience with EHR or EMR, I will use Maryland's Physician Licensure Database to ascertain whether the provider used an EHR or EMR from 2009 through 2012. Previous EHR or EMR use is restricted to 2009 because this is the first year that the Maryland Physician Licensure survey included this question.

Due to Medicaid EHR Incentive Program participation rules – which only allow a provider to participate in the Program once per year – this study will apply a one-year measurement pause or "contamination buffer." The "contamination buffer" is necessary because providers who have achieved "Meaningful Use" in calendar year 2013 likely acquired their EHR in calendar year 2012. However, the provider who acquired their EHR in 2012 could have done so at any point during that year. Because EHR implementation will likely impact provider

workflow and quality reporting, and the magnitude and duration of this impact will likely depend on the date on which the provider implemented the system, and the exact date of EHR implementation is not known, I will not use outcome measures during this year in the analytic model. However, this data will be used to during propensity score matching since it is collected before the intervention period.

Figure 5 shows this research design graphically, including the hypothesized results. To simplify the hypotheses, Figure 5 depicts a hypothetical scenario with a steady rate of average HEDIS® score growth for the comparison group over the time horizon of this study. The actual change in HEDIS® scores will depend on the data.

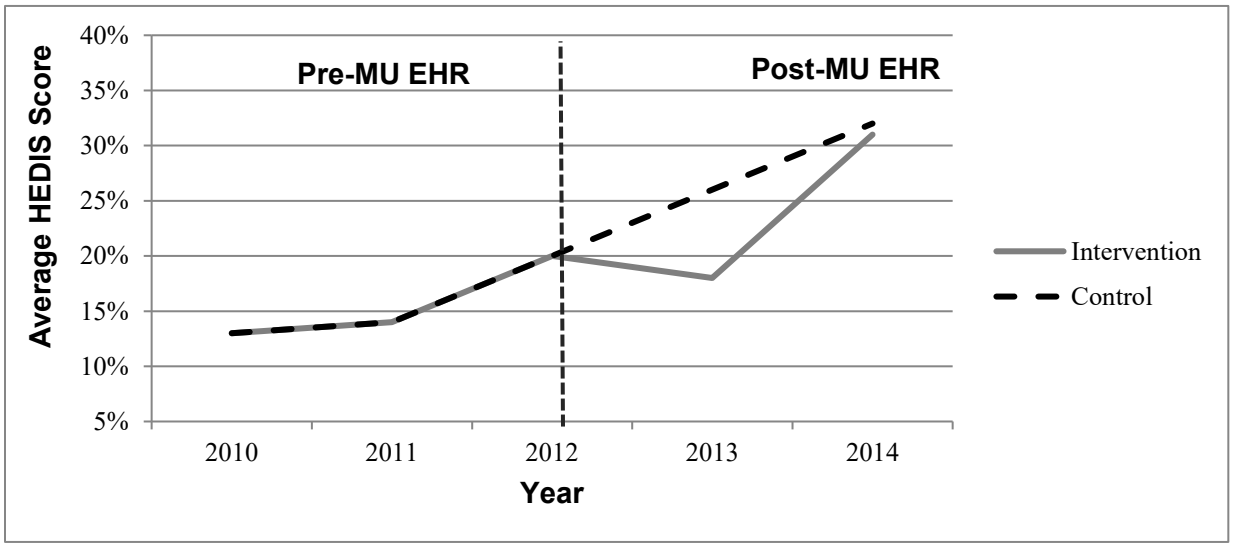


Figure 5: Hypothesized Graphical Representation of Study Results

The hypothesized results are that after acquiring an EHR and accounting for a contamination period of one year, **providers' quality scores will increase.** The Y-axis displays the average quality reporting for the intervention group (managed care network provider "EHR users") and the comparison group (managed care network provider "non-EHR users"). Although

not analyzed in this study, during the year of EHR acquisition (2012), the intervention group may experience a decrease in quality due to factors related to the "ramp-up" period, while the comparison group continues on their normal quality score trajectory.

CAUSAL MODEL

Using the HITREF framework to identify dimensions affecting successful Health IT implementation and the source and target model diagram to inform the research approach, Figure 6 depicts the causal model of variables impacting the main hypothesized relationship between "EHR Use", "Increased Quality", and "Increased Combination Immunization Score." As detailed in the "Variables and Measures" section below, I will take each variable depicted in Figure 6 into account when building my analytic model. EHR Use – as measured by "Meaningful Use" ("MU") – leads to increased immunization rates ("Increased Quality"), as measured by an increase in the HEDIS® combination score for immunization rates among children.

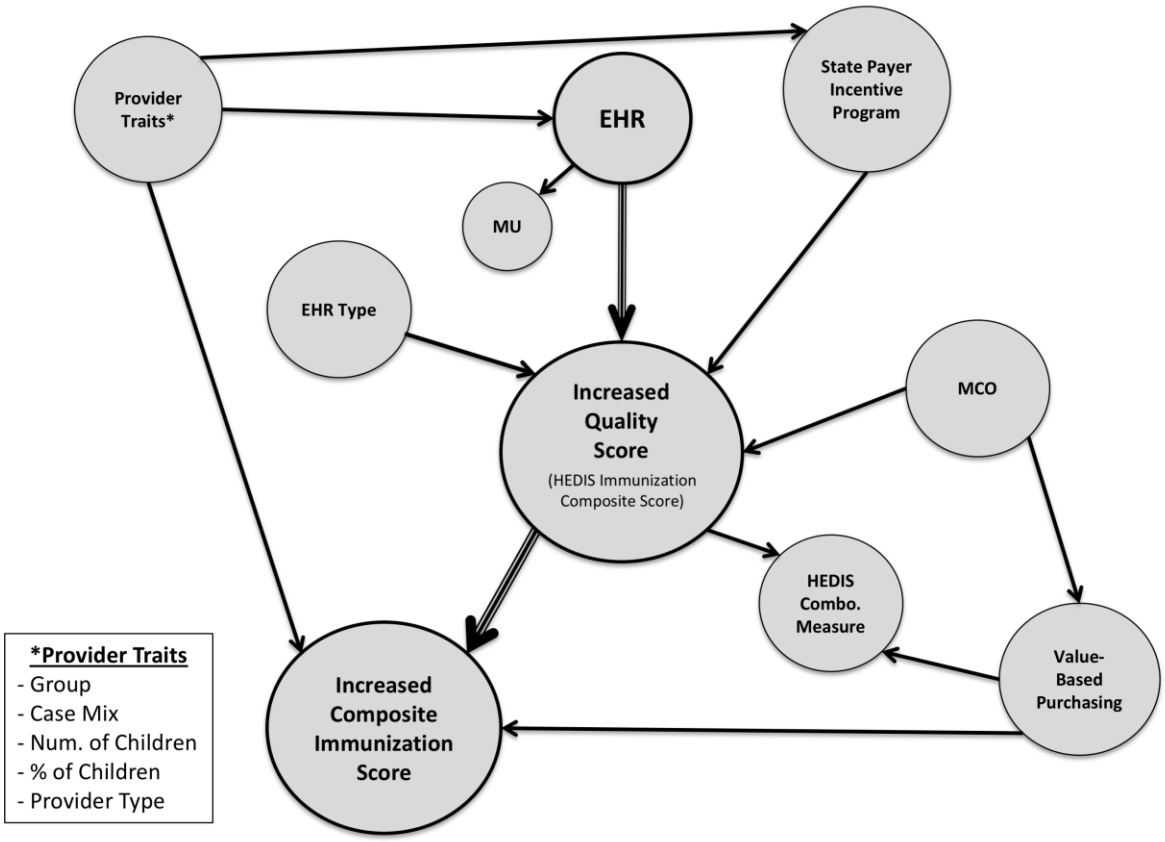


Figure 6: Presumed Causal Model of Variables Affecting the Relationship Between EHR Use and Quality Scores

The provider's "HEDIS® Combo. Measure" is a Maryland-specific VBP initiative that combines the immunization rates for DTaP, IPV, MMR, HiB, HepB, VZV, and PCV (Combination 3) and is pursued by every Maryland MCO. Because the "HEDIS® Combo. Measure" is a subset of the HEDIS® Combination Score, this analysis uses the combo measure to "check" on the relationship between EHR Use and the HEDIS® Combination score. If an individual's HEDIS® combo measure affects the relationship between EHR Use and the HEDIS® Combination Score, it may need to be included in the model as an effect modifier.

Motivational confounders, such as participation in VBP, the Vaccines for Children (VFC) program, and State-Regulated Payor EHR Adoption Incentive Program, may all impact the relationship between EHR use and quality, and thus must all be controlled for in the analysis. Many other incentive-based programs may exist for providers, such as the MHCC-administered Patient Centered Medical Home (PCMH), which, if not controlled for, may introduce bias. However, I could not obtain this information. As discussed in the Strengths and Weaknesses section, I attempted to mitigate this bias through the study design.

Although all MCOs participate in the VBP, MCOs may place different focus on various quality-improvement programs, such as immunization rates. Thus, a provider's MCO network affiliation may act as a confounder between a provider's immunization quality score and the presence of an EHR. This study does not control for the specific MCO that a provider participated with during the study period, nor the recipient's MCO affiliation. The reason I chose not to control for MCO affiliation is because of our focus on the provider as the unit of analysis. If I had introduced MCO affiliation at the provider and patient level, I would be analyzing the impact of the MCO and provider relationship on immunization status. Instead, this study analyzes the relationship between MCO network providers -- regardless of the specific MCO affiliation -- and the provider's patient panel recipient vaccination rates.

The VFC program provides free vaccines to providers in exchange for Maryland providers agreeing to follow childhood vaccine schedules. Thus, the providers participating in the VFC program can obtain all vaccines measured by the HEDIS® Immunization Status Score. The availability of this program may create an incentive for vaccine administration, both for the intervention and the comparison group.

Administered by MHCC, the State-Regulated Payor EHR Adoption Incentive Program required that State-regulated health care payors offer incentives to primary care practices for adopting and using certified EHR technology. Until 2014, the incentive included an $8 per member base incentive up to $7,500 per payor for the adoption of EHR technology. If the practice demonstrated advance use of the technology, they could receive up to an additional $7,500 per payor. In 2014, the program changed such that (1) primary care practices must either meet Meaningful Use or participate in any MHCC-approved Patient Centered Medical Home (PCMH) program and achieve NCQA PCMH recognition, and (2) the incentive would be calculated based on a $25 per member amount not to exceed $15,000 per practice per payor. The longitudinal nature of the research design will allow for the controlling of PCMH and State-Regulated Payor EHR Adoption Incentive Program participation (Maryland Health Care Commission, 2018).

Additional variables impacting the relationship between EHR use and quality include EHR type and Meaningful Use reporting period. Different EHRs may be more adept at aiding providers in meeting quality metrics due to usability. Further, depending on the time in which the provider adopted and then implemented their EHR in relation to their Meaningful Use reporting period may create an exposure confounder.

DATA AGGREGATION MAP

Building upon the analytic model depicted in Figure 6, Figure 7 provides a data aggregation map depicting the process I used to create the data set used in our analytic model. The data aggregation map begins with each data source used in the analysis, each data source's

data steward, the data from each source I used in this analysis, and any software used to query or aggregate the data.

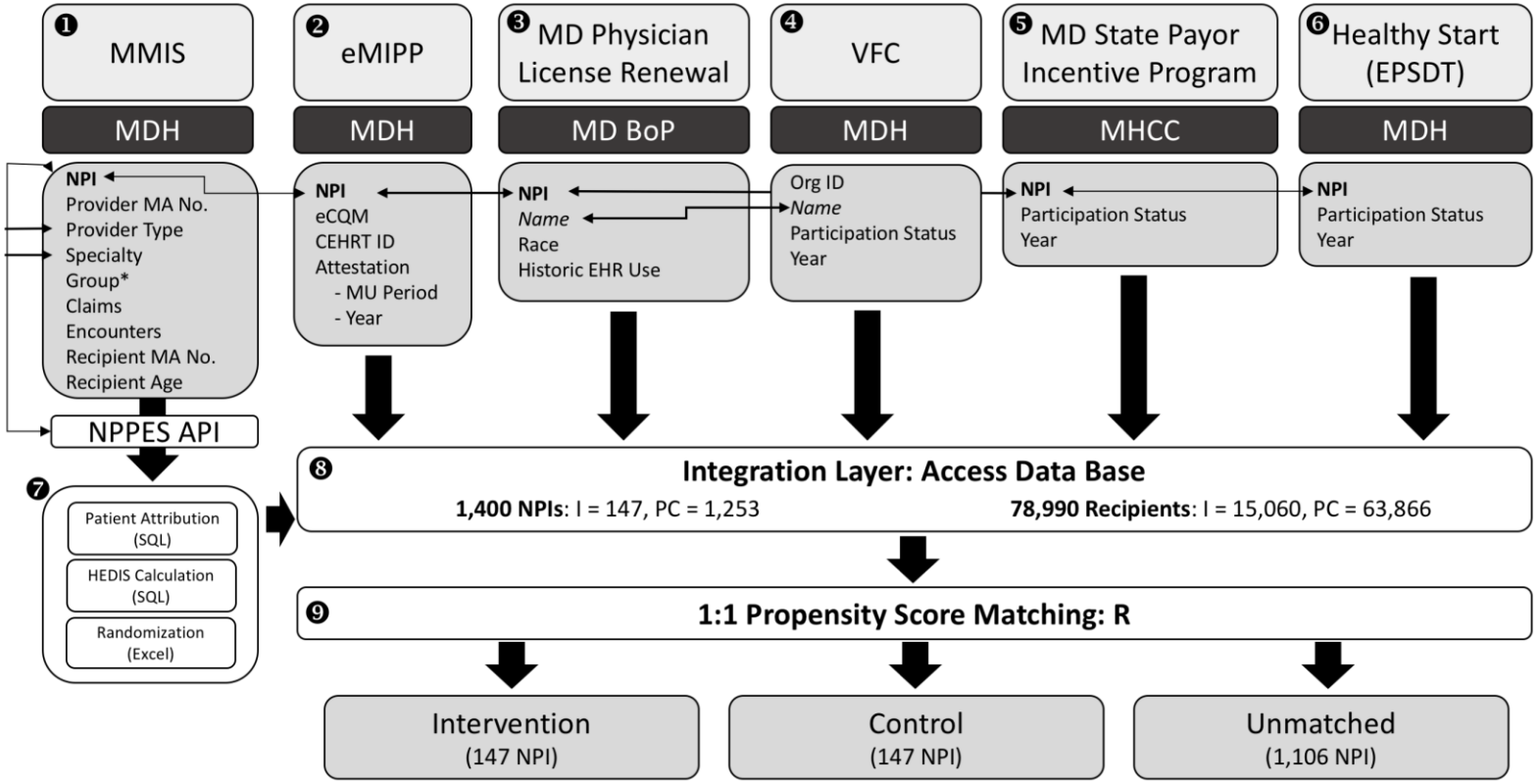
Throughout the remainder of Chapter 3, I will refer to Figure 7 when describing each step in the data cleaning and aggregation process. I will make references to Figure 7 using the numbered circles.

SOURCES OF DATA AND DATA STEWARDS

To obtain data for this study, I queried databases maintained within the Maryland Department of Health, the State of Maryland's Board of Physician's Database, and the Maryland Health Care Commission (MHCC). MMIS is Maryland Medicaid's claims payment and processing system. The system contains claims and encounters data and is used to calculate HEDIS®-type measurements for the Value-Based Purchasing (VBP) program (Figure 7, ❶).

Data related to the EHR Incentive Program, including participation, EHR type, and Meaningful Use measures is obtained from Maryland's EHR Incentive Program Registration and Attestation System, the eMIPP system (Figure 7, ❷).

The Maryland Board of Physician's Database contains licensure and survey data on all physicians licensed in Maryland. This data source is used to obtain demographic information on providers and will help to identify providers who self-identify as possessing an EHR (Figure 7, ❸).



** Group data comes from MMIS, but due to the additional time required to incorporate this logic into the query for all NPIs, the authors chose to perform the group affiliation query after initial data integration performed within Access.*

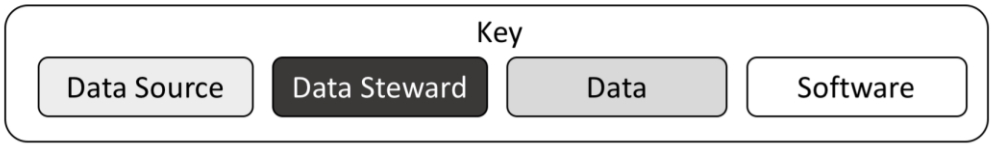


Figure 7: Data Aggregation Map

The Vaccines for Children Program (VFC) is administered by the Center for Immunization within the Prevention and Health Promotion Administration, an administration under the Maryland Department of Health (Figure 7, ❹). This data base contains data on provider immunization administration and participation in the VFC.

Since the MHCC is charged with operating the State-Regulated Payor EHR Adoption Incentive Program, data on provider participation and year of participation is obtained from the MHCC (Figure 7, ❺).

The Healthy Kids Program is Maryland's Early Periodic Screening, Diagnosis, and Treatment (EPSDT) Program. State-employed nurses visit pediatricians enrolled in Maryland Medicaid to certify them as meeting EPSDT standards, entering provider data into a local database overseen by the Maryland Department of Health (Figure 7, ❻).

PROPENSITY SCORE MATCHING

Because this research is observational and uses a quasi-experimental research method, I do not have a clear control group. One method for establishing a control group for quasi-experimental research designs is propensity score matching (PSM) (Figure 7,❾). PSM models the conditional probability of being selected for the treatment group given a series of confounders related to the outcome but not the treatment (Brookhart, Alan M., Schneeweiss, Sabastian, Rothman, Kenneth J., Glynn, Robert J., Avorn, Jerry, Sturmer, 2006; Rosenbaum, Paul R., Rubin, 1983). In observational studies where an intervention does not have a clear control group, such as would be the case with a randomize control trial, PSM can help to match observed pre-treatment assignment variables of individuals in the treatment group to those of a theoretical control group (Kaplan & Chen, 2012). By matching observed pre-treatment variables

of the treated and a control group, I may improve the likelihood that differences in outcome between intervention and control groups are due to the intervention alone and not unmeasured covariates. In other words, the more similar the intervention and treatment group are to each other on various characteristics before treatment, the more likely I am confident that I can better infer causal inferences between treatment and outcomes (Kaplan & Chen, 2012).

VARIABLES AND MEASURES

The variables used in this analysis, including their description, type, and sources, are listed in Table 1. A more detailed description of each variable and its measure are described below.

Table 1: Variables, Description, Type, and Source

Variable Type	Description	Data Type	Source
Dependent	Childhood Immunization HEDIS® Score	Proportional	MMIS (Figure 7, ❶)
Independent	Achieving Meaningful Use in the Medicaid EHR Incentive Program	Binary	eMIPP (Figure 7, ❷)
Covariates	Provider Specialty	Categorical	MMIS (Figure 7, ❶)
	Practice Medicaid Patient Volume	Nominal	MMIS (Figure 7, ❶)
	Outpatient Visits	Nominal	MMIS (Figure 7, ❶)
	Provider Race and EHR Use History	Binary, Categorical, or Nominal	BoP (Figure 7, ❸)
	Medicaid Child Case Mix (% of total Medicaid patients)	Proportional	MMIS (Figure 7, ❶)
	Participation in the State-Regulated Payor EHR Adoption Incentive Program	Binary	MHCC (Figure 7, ❺)
	Vaccines for Children Participation	Binary	MDH (Figure 7, ❹)

Variable Type	Description	Data Type	Source
	Healthy Kids (EPSDT) Participation	Binary	MDH (Figure 7, ❻)
	Time	Categorical (change point)	N/A
	HEDIS® Combo Score 3 and 7	Proportional	MDH

HEDIS®: Healthcare Effectiveness Data and Information Set
MMIS: Medicaid Management Information System
eMIPP: electronic Medicaid Incentive Payment Program
EHR: Electronic Health Record
BoP: Maryland Board of Physicians
MHCC: Maryland Health Care Commission
MDH: Maryland Department of Health
EPSDT: Early Periodic Screening, Diagnosis, and Treatment

Dependent Variable

The main outcome measure of "quality" is measured using an ambulatory provider-based version of the HEDIS® objective for childhood immunization status. This measure is expressed as a percentage of all eligible recipients during the year who receive various immunizations. The outcome measure used in this study is a version of Combination Measure 7, which requires that the following vaccines be administered before age 2: four diphtheria, tetanus and acellular pertussis (DTaP); three polio (IPV); one measles, mumps and rubella (MMR); two H influenza type B (HiB); two hepatitis B (HepB)[4], one chicken pox (VZV); four pneumococcal conjugate (PCV); two hepatitis A (HepA); and two or three rotavirus (RV).

I chose the childhood immunization quality metric because of the consistency of its use in the VBP program, its direct link to a Meaningful Use clinical quality measure, and the consistency in the Medicaid population during Health Care Reform.[5] Maryland Medicaid has

[4] HEDIS requires three Hep B vaccinations before age 2; however, this analysis only requires that a child receive two. See Table 2.

[5] As a result of the Affordable Care Act, States had the option to expand their Medicaid population to cover childless adults. Maryland Medicaid chose to participate in this expansion. The Medicaid expansion population of childless adults will likely not affect the childhood immunization measure, which is only applicable to children under age 2.

used this quality measure since at least 2009, and this quality measure is 1 of 7 VBP-based HEDIS® measures, making it financially important for Maryland Medicaid MCOs to ensure that their providers provide childhood immunizations. Further, because the childhood immunization quality metric does not rely exclusively on diagnosis codes, this study can be replicated longitudinally during the ICD-10 implementation period.

Table 2 lists each vaccination, the current procedural terminology (CPT) codes identified by HEDIS® to indicate the administration of each vaccination, and any details about vaccine administration or how its administration may have changed within the years of the study period, 2010-2014. All data used to calculate the outcome measure comes from MCO encounters submitted to the MDH over the study period (Figure 7, ❶, "Encounters").

Table 2: **Computable Phenotype Used to Identify Immunization Administration**

Immunization	CPT Codes	Notes
DTaP	90698, 90700, 90721, 90723	At least four vaccinations, with different dates of service on or before child's second birthday. Do not count any vaccines administered prior to 42 days after birth.
IPV	90698, 90713, 90723	At least three vaccinations, with different dates of service on or before child's second birthday. Do not count any vaccines administered prior to 42 days after birth.
Measles, Mumps, and Rubella (One of the below options)		
MMR	90707, 90710	At least one vaccination with service on or before child's second birthday.
Measles and Rubella ***AND*** Mumps	90708, 90704	At least one of each vaccination with service on or before child's second birthday.

Immunization	CPT Codes	Notes
Measles ***AND*** Rubella ***AND*** Mumps	90705, 90706, 90704	At least one of each vaccination with service on or before child's second birthday.
HiB	90645-90648, 90698, 90721, 90748	For 2010 At least two vaccinations with different dates of service on or before child's second birthday (due to shortage).
Hep B*	90723,90740, 90744, 90747, 90748	At least two vaccinations with different dates of service on or before child's second birthday.
VZV	90710, 90716	At least one with service on or before child's second birthday.
Pneumococcal conjugate (PCV)	90669, 90670†	At least four vaccinations, with different dates of service on or before child's second birthday. Do not count any vaccines administered prior to 42 days after birth.
Hep A	90633	For 2010 - 2012 Two vaccinations with different dates of service on or before child's second birthday. For 2013 and 2014 One dose on or before child's second birthday.
Rotavirus (One of the below)		
Rotavirus 2	90681	Two vaccinations with different dates of service on or before child's second birthday. Do not count any vaccines administered prior to 42 days after birth.
Rotavirus 3	90680	Three vaccinations with different dates of service on or before child's second birthday. Do not count any vaccines administered prior to 42 days after birth.

*HEDIS and Maryland's Healthy Kids program specifies three vaccinations. However, because the first dose frequently occurs at birth within the hospital, and this analysis is measuring vaccine rates associated with PCPs in an office-based setting, the number of minimum vaccines required is reduced to two.

†In mid-2011, CDC recommended the use of PCV13, documented with CPT code 90670. New conjugate available on or around 2011.

Some children may not receive vaccinations due to contraindications. Vaccine contraindications are conditions that increase the risk that a patient will experience a severe adverse reaction to the administration of a vaccine. Based on the diagnosis codes listed in Table 3, children are removed from the denominator of specified immunization HEDIS® scores. To account for contraindications, I searched Medicaid MCO encounter history for the diagnosis codes listed in Table 3 from any recipient's prior Medicaid encounter history. Since each child's immunization status is checked from birth through age two, this means that encounter history is searched for contraindications for any date of service from 2009 through 2014. If a Medicaid encounter contains any ICD-9 code listed in Table 3, that child is removed from the denominator of the mapped immunization.

Table 3: **Contraindications for Children Eligible to Receive Vaccinations**

Immunization	ICD-9 Code
DTap	323.51 with (E948.4 or E948.5 or E948.6)
MMR, VZV	279 or 042 or V08 or 200-208

Between 2010 and 2014, Maryland MCOs averaged a 36.8 percent reportable rate for Combination 7 (HealthcareData Company, 2014). This relatively low compliance rate compared to a theoretical 100 percent reportable rate reduces the likelihood that participants in this study will experience a "ceiling effect" during the study period. MDH's contractor, HealthcareData Company, LLC, collects, calculates, and reports Maryland Medicaid's HEDIS® scores. All measures collected follow national standards, which allow for cross-plan comparisons. The development and wide-use of these measures makes them highly valid and reliable.

Although Maryland collects HEDIS® data on 21 measures a year, only a handful of HEDIS® measures are used for the Department's VBP program. Immunization Status Score, Combination 7 is not one of the 10 quality metrics used by MDH's VBP; however, the MDH does include Immunization Status Score, Combination 3. Due to the financial incentive and disincentive associated with immunization administration, there is likely to be greater attention paid to the accuracy and completeness of relevant data among MCOs and their network providers. To check the reasonableness of the HEDIS® scores calculated, I referenced the Maryland MCO HEDIS® Combo 3 and Combo 7 scores for each study period.

Active Independent Variable

Active independent variables include a binary variable on whether a provider implemented an EHR and received payment for participating in Maryland Medicaid's EHR Incentive Program in 2013. Depending on the type of EHRs used and whether there is any variability between quality and EHR type, this study utilizes a categorical variable for EHR vendor deployment type, either cloud-based, client/server-based, or both.[6] To identify Medicaid providers who have implemented an EHR, this research uses the data from Medicaid's EHR Registration and Attestation System (eMIPP) (Figure 7, ❷). This data repository stores information on participants in the EHR Incentive Program.

The reliability and validity of EHR Incentive Program Year participation and EHR Certification Number, vary. The binary variables for EHR implementation and EHR system are based on self-reported data by providers during the attestation process for participation in the

[6] To categorize the type of EHR implemented, I used the eMIPP system and an EHR Certification Number crosswalk that maps the certified system to a product description. The CMS Certification Number is a unique 15 alphanumeric string that identifies the EHR product as "complete" ("monolithic") or "complete because of additional modules" ("modular"). Because all providers in the intervention group use complete/monolithic products, the categorical variable used in this analysis will control for EHR vendor product deployment type.

Medicaid EHR Incentive Program. Although some providers may be audited for the validity of their attestation, this research does not take this into account. Thus, it is assumed that all providers who attest to implementing an EHR have actually done so. It is also assumed that the provider correctly selects their CMS Certification Number. However, there is likely no difference between the likelihood of any one provider or provider type to misreport this information, thus the reliability of both variables is likely sound.

Intervening Variables (Non-Propensity Score Matching Variables)

The non-Propensity-Score-Matching variables that act as intervening variables – participation in the State-Regulated Payor EHR Adoption Incentive Program, prior EHR use, and predominant health care group affiliation – are obtained from various sources and are likely reliable and valid measures.

The Maryland Health Care Commission (MHCC) provided data used to ascertain participation in the State-Regulated EHR Incentive Program by year, using the data listed in (Figure 7, ❺). The HEDIS® immunization status score used as a check on the outcome measure is obtained from administrative data published by MDH following a review by the Department's measure validation vendor, Healthcare Data Company LLC. Primary provider group affiliation is derived from MMIS (Figure 7, ❶), using an iterative approach described elsewhere in this research.

Provider participation in the State-Regulated EHR Incentive Program, the EHR Incentive Program and with MCOs are controlled by contracts, impact payments, and are subject to post-payment audits, so information contained in these databases will be accurate. HEDIS® Combination Scores are rigorously reviewed before being approved by MDH and are thus likely reliable and valid. The Meaningful Use reporting period is also reliable and valid, as providers

must produce Meaningful Use reports to substantiate that they have met Program requirements. These reports are submitted to Medicaid during attestation.

Propensity Score Matching Variables

The provider-level characteristics of specialization, Vaccines for Children (VFC) and Healthy Kids (EPSDT) participation, and group size and child visit caseload are available from MCO and Medicaid Fee-For-Service (FFS) administrative and claims data, respectively (Figure 7, ❶). This information should be both reliable and valid, as all are required elements to finalize contracts between the MCO and the provider. Additionally, claims data, which is used to calculate case load, is reliable and valid, as it results from robust pre-payment validation checks against both provider and recipient data. Provider specialty is also crosschecked with the State Licensure Board during MCO enrollment, and when there is a conflict with provider specialty across MCO or time, I cross-referenced the provider's National Provider Identifier (NPI) against the Center for Medicare and Medicaid Services National Plan and Provider Enumeration System (NPPES).

Percent of Medicaid patient case mix is expected to be reliable and valid. Medicaid FFS pre-payment provider and recipient screening is robust, and its annual post-payment auditing of MCO encounters rigorously checks provider and patient information. Although providers must submit percent Medicaid patient volume during a typical quarter for the calendar year previous to participation in the EHR Incentive Program, this is still a self-reported measure. However, the measure is likely reliable across provider types, as there is no reason to believe that any one provider type systematically over or under reports their Medicaid patient volume percentage.

STUDY POPULATION AND SAMPLE

Thus far, this chapter has described the source of data, its data steward, and data elements. This section describes the selection of the study population. The EHR Incentive Program pays providers an incentive for adopting and then "meaningfully using" their certified EHR. Providers participating in the program can be any non-hospital-based provider,[7] which includes those in both solo and group practices. Although individual providers receive the incentive, it is the practice that installs the EHR. Thus, there are three levels of data collection, occasions (time period), the provider, and the practice. The unit of analysis for this study is the provider.

[7] The federal agency with rulemaking authority for the EHR Incentive Program, Centers for Medicare and Medicaid Services (CMS), defines "hospital-based provider" as any provider who sees over 90 percent of their covered professional services in the inpatient or emergency department.

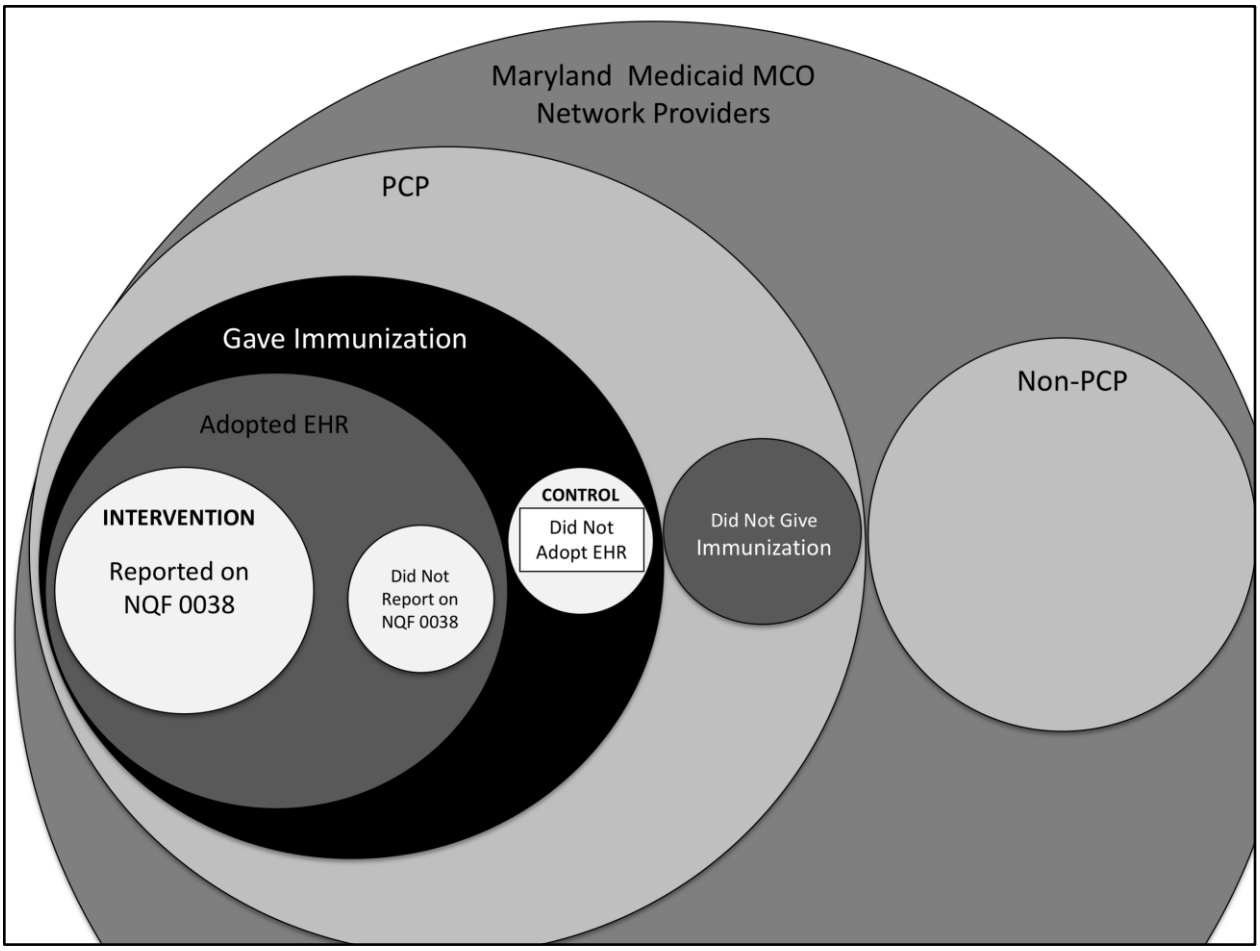


Figure 8: **Study Sample Selection**

As shown in Figure 8, the study population is any Maryland Medicaid MCO primary care network physician that is continuously enrolled in an MCO over the four-year study period, gives immunizations, adopts an EHR, achieves Meaningful Use in 2013, and reported on Clinical Quality Measure (eCQM) NQF 0038 "Childhood Immunization Status" (N=147).

The providers who attested to meeting eCQM NQF 0038 are compared to primary care physicians who give immunizations, but do not adopt an EHR. In Figure 8, the populations that will be compared are labeled "Intervention" and "Comparison." For the Intervention and Comparison groups, data from MMIS will be used to calculate the NQF 0038 Combination 7 HEDIS® score.

To operationalize the identification of intervention and comparison group providers I performed the following steps, described below and depicted in (Figure 7, ❼).

Providers potentially eligible for inclusion in the intervention group are those physicians who attested and received payment for meeting programmatic requirements for the Maryland Medicaid EHR Incentive Program in calendar year 2013 and also reported on the electronic Clinical Quality Measure (eCQM) NQF 0038 "Childhood Immunization Status" (n=210). Then, the National Provider Identifiers (NPI) for these providers are checked against Maryland Medicaid's historic Managed Care Organization (MCO) provider network file to obtain MCO network enrollment spans for calendar years 2010, 2011, 2012, 2013, and 2014.

Mimicking HEDIS® requirements for the "Childhood Immunization Status" specifications, the enrollment spans for each NPI are analyzed to select only those NPIs where there is no more than a 30-day consecutive lapse in provider enrollment across all MCO with which the provider is enrolled. Of these providers, only those who are physicians and are designated as Primary Care Providers (PCP) by an MCO are selected. To ensure that only individual physicians are eligible to be comparison group providers, I used an Application Program Interface (API) call to NPPES to validate provider status and provider type (Figure 7, ❶). This process resulted in 147 physicians in the intervention group and a potential 1,272 providers eligible for the comparison group. Providers are selected for the comparison group after Propensity Score Matching (PSM) (Figure 7, ❾). The study population is restricted to physician PCPs, instead of other provider types eligible for PCP designation in Maryland Medicaid, such as nurse practitioners, because I only obtained covariates from the Maryland Board of Physicians (Figure 7, ❸).

After establishing the intervention and potential comparison group, I identified all Medicaid children who turned two years during one of the intervention years (2010 – 2014) (Figure 7, ❼). Following HEDIS® inclusion logic, from this pool of children, each child's enrollment in a MCO is calculated such that those children with more than a 1-month (30 day) gap in coverage are dropped. The children who have less than a 1-month gap in coverage are sorted based on their earliest Evaluation and Management (E&M), preventative medicine CPT code, restricted to only initial preventative medicine visits for ages less than 2. The use of E&M codes for passive patient attribution has been used by Medicare for quality reporting in the Physician Quality Reporting System (PQRS) (Dowd, Li, Swenson, Coulam, & Levy, 2014). Similarly, Pham et al. used the number of billed E&M codes to passively attribute patients to primary care physicians in order to analyze care coordination between PCPs and other Medicare physicians (Pham et al., 2009).

Table 4 provides the descriptions for CPT codes 99381, 99382, 99391, and 99392. The CPT codes in Table 4 are used as binding codes to link a recipient to a PCP. I chose these codes because they represent the child's first, outpatient visit with a PCP. Because Medicaid may not necessarily confirm that a child's visit is initial versus periodic (e.g., CPT code 99381 versus 99391), I included codes 99391 and 99392. However, CPT codes 99391 and 99392 are only used to bind a recipient to a PCP if encounter history does not reveal an earlier 99381 or 99382 code. The resulting analysis produced 78,922 children affiliated with a unique MCO network physician, 147 of which are in the intervention group and 1,253 potential comparison group candidates.

Table 4: **Evaluation and Management Codes Used For Patient Attribution**

CPT code	Description
99381	Initial comprehensive preventive medicine evaluation and management of an individual including an age and gender appropriate history, examination, counseling/anticipatory guidance/risk factor reduction interventions, and the ordering of laboratory/diagnostic procedures, new patient; infant (age younger than 1 year).
99382	Initial comprehensive preventive medicine evaluation and management of an individual including an age and gender appropriate history, examination, counseling/anticipatory guidance/risk factor reduction interventions, and the ordering of laboratory/diagnostic procedures, new patient; early childhood (age 1 through 4 years).
99391	Periodic comprehensive preventive medicine reevaluation and management of an individual including an age and gender appropriate history, examination, counseling/anticipatory guidance/risk factor reduction interventions, and the ordering of laboratory/diagnostic procedures, established patient; infant (age younger than 1 year).
99392	Periodic comprehensive preventive medicine reevaluation and management of an individual including an age and gender appropriate history, examination, counseling/anticipatory guidance/risk factor reduction interventions, and the ordering of laboratory/diagnostic procedures, established patient; early childhood (age 1 through 4 years).

Following the binding of children to PCPs, the author bifurcated PCPs into intervention and potential comparison candidates. These providers are either (1) providers who participated in the Medicaid EHR Incentive Program in calendar year 2013, reported on the electronic Clinical Quality Measure (eCQM) NQF 0038 "Childhood Immunization Status," is a PCP for at least one MCO throughout the study period and provides immunizations (the "intervention group") or (2) a physician, designated as a PCP by at least one MCO, and provides immunizations (the "eligible comparison group").

DATA CLEANING AND LINKING

Selecting Records and Merging Data Sets

This analysis combines six data sources: Maryland Medicaid Information System (MMIS); Maryland's electronic Medicaid Incentive Payment Program (eMIPP); Board of Physicians; State Payor EHR Incentive Program; Vaccines for Children Program (VFC); and Healthy Kids, Maryland's Early Periodic Screening and Detection Program. Each data source is identified in Figure 7, ❶ – ❼, with the arrows showing the data linkages. The National Provider Identifier (NPI) – a unique, provider-specific identifier, self-attested to by every health care provider via the National Plan and Provider Enumeration System (NPPES) – is the primary key used to combine all data sets. All source records for each data set utilizes the NPI to track records except Maryland's VFC program.

To maintain anonymity during analysis, each recipient Legacy MA Number and provider NPI is assigned a randomly generated numeric identifier after the data is linked.

Maryland Medicaid Information System Data

The base data set is the MMIS data obtained on PCPs, their recipients, and their vaccine status. The initial MMIS data query contained 65,534 recipients and 1,711 unique providers. To ensure that only individual physicians with NPIs known to NPPES are included in the analysis, I used the NPPES Application Program Interface (API) to validate provider type, status (active or inactive), and NPI type (Type I (individual) providers only. Additionally, I compared provider type and specialty codes across MCOs and with NPPES where necessary to confirm a single provider type and specialty for each provider. Inconsistencies between providers' provider type and specialty occasionally arose due to an MCO designating a provider as a specialty using an

outdated internal Medicaid specialty code or due to the MCO designating a provider's specialty as something other than what the provider enumerated in NPPES. This process reduced the number of records to 78,990 recipients and 1,400 unique, physician NPIs.

To calculate the outcome measure – the HEDIS-like immunization quality score – I obtain the encounter and claims history for all recipients who are linked to PCPs using E&M codes. The process of retrieving this information is described above. Recipients are tracked within MMIS using Medical Assistance Numbers (MA Numbers or Recipient IDs). Medicaid recipients may have more than one MA number; however, all MA Numbers are linked to the first MA Number received by a Maryland Medicaid recipient -- a Legacy MA Number. Each time a recipient received a particular vaccine at the designed time interval, the PCP associated with that recipient is credited with administering the vaccination. By vaccine and by calendar year, the counts of recipients assigned to the PCP receiving the vaccine are summed, as are the total number recipients assigned to the PCP. Using this process, I can obtain vaccination rates by provider by vaccination. To obtain vaccination combination scores, the appropriate vaccine counts are summed and a ratio of vaccination to total affiliated recipients by PCP is calculated. Equation (1) details the vaccination combination score calculation, with *nPatient(PCP)* being the number of patients associated with a particular PCP.

$$(1)\ \text{HEDIS® Score}\ (\text{PCP}_i) = \frac{\sum_{j=1}^{\text{nPatient}(\text{PCP}_i)} \sum_{k=1}^{\text{nVaccines}} \text{I}(\text{pt}_j \text{ received vaccine k in time interval(k)})}{\text{nPatient}(\text{PCP}_i)}$$

Note: I(p) = 1 if p is true, 0, if false.

Maryland's electronic Medicaid Incentive Payment Program (eMIPP)

To obtain the intervention group, I queried eMIPP for physicians who attested and received payment for meeting programmatic requirements for the Maryland Medicaid EHR Incentive Program in calendar year 2013 and also reported on the electronic Clinical Quality Measure (eCQM) NQF 0038 "Childhood Immunization Status" (n=588). Since I wanted to analyze only those providers who selected the NQF 0038 "Childhood Immunization Status" measure and actually reported administering a vaccination, I removed from the analysis providers reporting blank numerators, which reduced the sample to 210. After linking this data set via NPI to the claims and encounter query, a total of 147 providers remained. I dropped 63 providers from the eMIPP file because they failed to meet HEDIS® inclusion criteria or did not acquire at least one patient during attribution.

Board of Physicians

The Maryland Board of Physicians license renewal database provided the following data used in this analysis for the years 2009-2014: National Provider Identifier (NPI), Race, EHR use. I used the NPI to link records. I used the Race variable as a covariate. For years 2009-2012, the Maryland Board of Physicians coded "Race" in a single seven-character string, with each character having a binary value of "0" or "1" for whether or not the physician self-reported as being a specific race. For the period 2013-2014, the Maryland Board of Physicians changed their approach to the "Race" variable but storing the same race numeric string positions in separate fields, instead of a single string. Because the position of each race description remained the same across all years, I concatenated the 2013-2014 values into a single string. I identified 21 unique

concatenated race values across all providers and years. Based on frequency distributions across these 21 unique race values, I created five categorical race bins, as show in Table 5.

Table 5: **Recoded Physician Race Variables, Description and Frequency**

Race	Description	Categorical Variable	Frequency
White	Any physician selecting "white."	1	44%
Asian	Any physician selecting "Asian," except those also selecting "White."	2	21%
Native Hawaiian/Pacific Islander	Any physician selecting "Native Hawaiian or Pacific Islander", except those selecting either "White" or "Asian."	3	16%
Other	All other "Races"	4	4%
Unknown	Any provider that did not answer the "Race" question.	5	16%

Note: N=1,400.

To determine past use of an Electronic Health Record (EHR), I used the Maryland Board of Physician's licensure renewal survey question that asks at your primary practice location, "Are Electronic Health Records (EHR) used?". The Maryland Board of Physicians used the same question, provided the same answer choices, and coded those answers in the same way from 2009-2014. Providers could choose "All Electronic," "Part paper and electronic," "No," and "Do not know." I coded providers who selected "All Electronic", and "Part paper and electronic" as "1" and all others, "0".

State Regulated Payor EHR Adoption Incentive Program

The Maryland Health Care Commission (MHCC) administers the State Regulated EHR Adoption Incentive Program. The administrative data collected by MHCC records data on provider participation within certain time periods: October 2011-April 2013; May 2013-December 2013; January 2014-September 2014; October 2014 - March 2015; and April 2015-September 2015. Due to administrative data collection, it is impossible to determine what month or year a provider participated within a given bin. For example, a provider participating in November 2011 is indistinguishable from a provider participating in March 2013, since both hypothetical providers would show up in administrative data as participating during the period "October 2011 – April 2013".

Because this analysis uses calendar year as the standard measurement for all other variables, the State Regulated Payor data needed to be divided into calendar year. Additionally, because the administrative data are not equitably distributed within or over a calendar year, I could only use January 2014 as a natural calendar break point. Thus, I created two binary variables for determining participation with the State Regulated Payor EHR Adoption Incentive Program, one for the period October 2011 – December 2013 and one for the period January 2014 – March 2015. Providers participating at any time between October 2011 and December 2013 are coded with a "1", all others receive a "0". Providers participating at any point between January 2014 and March 2015 are treated as if they participated only in Calendar Year 2014.

Vaccines for Children

Maryland's VFC program uses an Organization Identifier, which tracks the practice location to which various vaccines are provided and stored. To incorporate provider VFC

participation data into the master data set used for this analysis, I de-duplicated VFC participation by primary provider contact for each Organization ID. Then, using first and last name matches within Microsoft Access, I pulled NPIs from all other data sets. If after leveraging current data sets I could not find an NPI, I searched the NPPES registry using the search criteria of first and last name and participating state of Maryland. For each calendar year, I assigned a binary variable to designation participation in the VFC program. A total of 470 providers could be linked to an Org. ID in the VFC data base as participating with the VFC program.

Early Periodic Screening, Diagnosis, and Treatment (EPSDT)

The Maryland Healthy Kids Program (Healthy Kids) certifies provides EPSDT Certification for Maryland Medicaid providers. The Health Kids Program certifies providers once, applying a certification date to certified provider records within their native database. Using the NPI from this database, I linked providers and determined EPSDT status in the following way: Providers receive a "1" in the year they are EPSDT certified and every year thereafter. For example, if the Healthy Kids Program certified a provider in 2006, the provider would be coded as being EPSDT certified for the period 2010-2014.

GROUP AFFILIATION

All intervention and potential comparison group providers participate with multiple groups with a varying number of group members over time. This means that there will be varying degrees of confounding among group members of the estimated effect of EHRs on quality. Thus, the analytic model chosen must account for group-based confounding. A "group" is defined as any provider who practices under and is affiliated with a Type 2 "Organization"

National Provider Identifier (NPI) in Maryland Medicaid. To account for location-based confounding, the Medical Assistance (MA) number is used in place of the NPI to establish group affiliation (data obtained as shown in Figure 7, ❶ and data linking occurs at ❽). The MA number is a unique 9-digit number that contains a 7-digit base number and a 2-digit location code.

Because providers practice with many groups, and because this analysis recognizes that the intervention group is comprised of providers who use an EHR at a physical practice location, I restricted each provider in each calendar year to a primary group. For the intervention group, in calendar year 2013, the group to which they are primarily affiliated is represented by the pay-to MA number to which they released their Medicaid EHR Incentive. For all other periods and for all comparison group periods, I used an iterative approach to identify primary group affiliation, based off of data in the Fee For Service (FFS) MMIS file. Although this analysis focuses on MCO network providers, MCOs do not report to Medicaid the group to which they maintain a contract. Rather, they report their networks by individual providers.

To identify all other primary group affiliations but those for the intervention group in calendar year 2013, I queried the FFS MMIS file for any group affiliations. The FFS MMIS file records begin- and end-date fields for all group MA numbers to which a provider is affiliated. Next, by calendar year, I counted the number of days a provider is affiliated with a group from the initial begin date of the group affiliation to the lesser of the date within the calendar year or the end of the calendar year. By calendar year, the group with the greatest number of days in which the provider is affiliated is marked as the provider's primary group. In the event that no group solely accumulates the greatest number of affiliated days, I next checked for the earliest begin date of the association between the provider and each group. If a tie still resulted, I

selected the group with a current active billing status with Maryland Medicaid. If the tied groups each had an active enrollment status code, I picked the group with the earliest active enrollment begin date. If the tied groups each had a current inactive status code, I picked the group with the latest inactive begin date.

Table 6 below shows the descriptive statistics on group membership, comparing the intervention group of providers to the PSM-selected comparison group of providers, using the method described above. Although group membership affiliation occurred before PSM calculation, since group membership was not a covariate for matching, only post-PSM match results are shown. Across all years, the individual providers in the intervention and comparison groups tended not to be primarily affiliated with any other respective intervention or comparison group providers. This is shown by the high frequency of providers with no additional member within their respective group. However, if providers were primarily affiliated with other respective intervention or comparison group providers, group membership tended to be higher among the intervention, as compared to the comparison group.

Additionally, the number of providers affiliated with a similar group tended to be consistent across all time periods for the comparison group; however, for the intervention group, the same pattern held true, except for the intervention year, 2013. This collapsing of unique group numbers is likely due to the change in methodology for establishing group affiliation in this year and the fact that group practices who may not have been the primary practice location for intervention group providers moved to claim EHR Incentive Payments from rendering providers during the EHR Incentive Program attestation.

Table 6: **Descriptive Statistics of Physician Group Affiliations, by Intervention, Comparison, and Time**

	Number of Unique Groups	Group Sizes				Max. No. of Providers per Group
		1	2-6	7-11	12+	
CY 2010						
Intervention	112	104	6	1	1	13
Comparison	138	131	7	0	0	4
CY 2011						
Intervention	112	104	6	1	1	13
Comparison	135	125	10	0	0	4
CY 2012						
Intervention	107	96	8	2	1	14
Comparison	134	124	10	0	0	3
CY 2013						
Intervention	63	46	15	1	1	19
Comparison	135	125	10	0	0	3
CY 2014						
Intervention	109	98	9	1	1	14
Comparison	134	125	9	0	0	4

Because data are collected at both the provider and practice level, and because different providers may participate with the same practice, observations will likely be correlated, leading to biased estimates. In multi-level modeling, sample size is important for evaluating standard errors both at the individual and group level. For this study, all eligible providers will be included, thus reducing the concerns about the individual-level sample. Based on simulations, Maas and Hox (2005) note that large group numbers appear more important than large number of individuals within groups. Further, standard errors of group-level variances are underestimated with groups less than 100, but group numbers between 50 and 100 produce acceptable group-level standard errors (Maas & Hox, 2005).

PROPENSITY SCORE MATCHING

After integrating data sources within Access (Figure 7, ❽), I created a comparison group using R's MatchIt (http://gking.harvard.edu/matchit) package using the nearest neighbor approach, without replacement (Figure 7, ❾). The Match It package derives a propensity score, which acts as a "balancing score," comparing treatment to comparison. So long as the treatment and comparison groups resulting from MatchIt produce balanced data, the resulting treatment and comparison panels should reduce the potential for bias, lower variance, and lower mean squared error in subsequent analysis using this panel (Ho, Imai, King, & Stuart, 2007, 2011). In practice, this means that MatchIt does not produce a treatment-comparison "pair," but instead impanels the data to improve balance between treatment and comparison groups by minimizing the difference between treatment and comparison propensity scores. A provider's score, then, summarizes all the measured covariates associated with that provider's having chosen to use an EHR or not, and can be used as a covariate (confounder) in models looking for the impact of EHR on HEDIS® scores.

Koepke et al. used surveys to identify provider and patient characteristic that correlated with child immunization rates (2001). Following Koepke et al.'s work, I analyzed provider characteristics such as practice size, provider specialty, participation in VFC on childhood vaccination rates, finding the strongest correlation with provider type (Koepke, Vogel, & Kohrt, 2001). For this research, PSM is operationalized by comparing the intervention group to the potential comparison group, scoring the likelihood to adopt an EHR matching against data by each calendar year on: provider primary group affiliation (calendar years 2010-2012), EPSDT certification status (calendar years 2010-2012); provider specialization; participation in the Vaccines for Children's Program (VFC), total Medicaid claims and encounter volume (calendar

years 2010-2012); percent of Medicaid claims and encounter volume for children under 2 years of age (calendar years 2010-2012); percent of Medicaid claims and encounter volume between the ages of 3 and 18 (calendar years 2010-2012).

I chose to conduct PSM at the individual provider level (controlling for group membership) instead of creating propensity scores at the provider-cross-group level because (1) all covariates are obtained at the provider level and (2) the method for and nature of provider group affiliation makes it difficult. As explained above, group affiliation is based primarily on longevity of affiliation. Because a provider who participates in the EHR Incentive Program could receive an EHR Incentive Payment for installation and use of an EHR at any practice at which they participate, there is an unknown correlation between group attribution and EHR acquisition and use. Additionally, provider group affiliation and the elective nature of the EHR incentive program make it such that a single group could have both intervention and comparison members. Finally, as shown in Table 6, the vast majority of groups comprised only one member.

The MatchIt package provides various methods for determining the type of matching and the fitness (or balance) of the comparison group. To determine fitness of the PSM dataset, I used either MatchIt or Cobalt (https://github.com/ngreifer/cobalt) to run a series of balance diagnostics, including differences in means, comparing treatment and potential comparison groups, a covariate balance chart ("love plot") comparing absolute mean differences by variable pre- and post-matching, and quantile-quantile plots (QQ plots) (Ho et al., 2011).

The first task was to decide on a match ratio. I evaluated matching approaches using the percent balance improvement, comparing the mean distance difference, comparing matched data to unmatched data. Using the nearest neighbor approach without replacement, I calculated a 1:1 match ratio of treatment to comparison, a 1:3 match ratio, and a 1:5 match ratio. The percent

balance improvement of the mean distance difference dropped off as the match ratio increased, beginning with 98.01for the 1:1 match ratio, 92.94 for the 1:3 match ratio, and 66.05 for the 1:5 match ratio.

After selecting the advantageous 1:1 nearest neighbor without replacement match ratio, I created QQ plots, comparing the quantiles of the treatment group against the quantiles of the matched comparison group (see Appendix 1). These variable-by-variable comparison plots generally showed clustering along a straight 45 degree line, providing strong evidence that the distributions for the matched treatment and comparison groups are uniform (Ho et al., 2011).

Calculated in another way, a balance table, compares the mean difference for each variable used in matching, pre- and post-matching algorithm. At a 0.1 mean difference threshold, only three variables[8] remained unbalanced post matching, though the difference in the distribution of these values, comparing treatment to pre-PSM matching is not excessive (see Appendix 2).

Figure 9 depicts the propensity score distribution for the 1:1 nearest neighbor approach, providing strong evidence that the propensity for selected providers to obtain an EHR based on the covariates used in matching are similarly distributed.

[8] *PV_10_Less2_Prt*, *PV_11_Less2_Prt*, and *PV_11_3_18_Prt.*

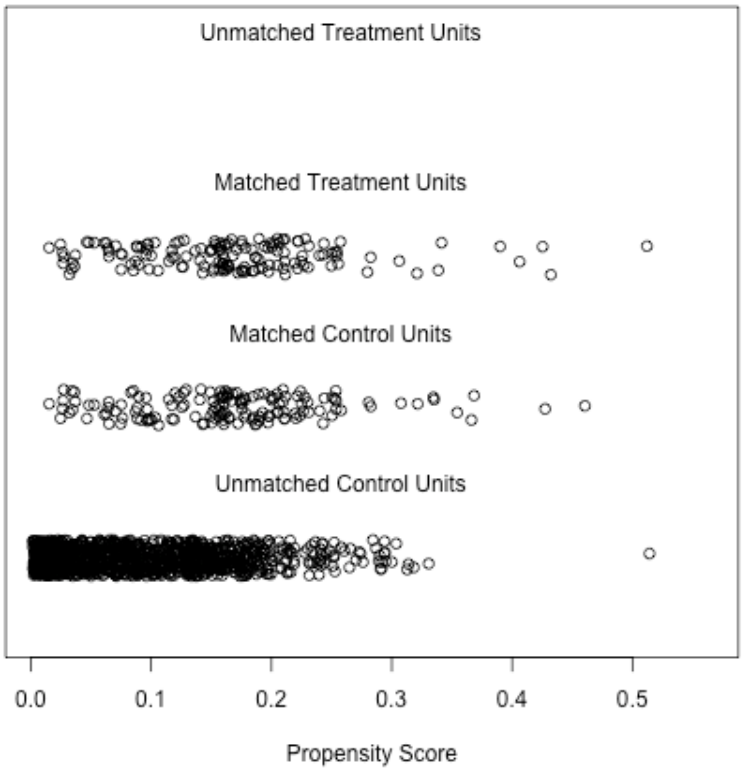
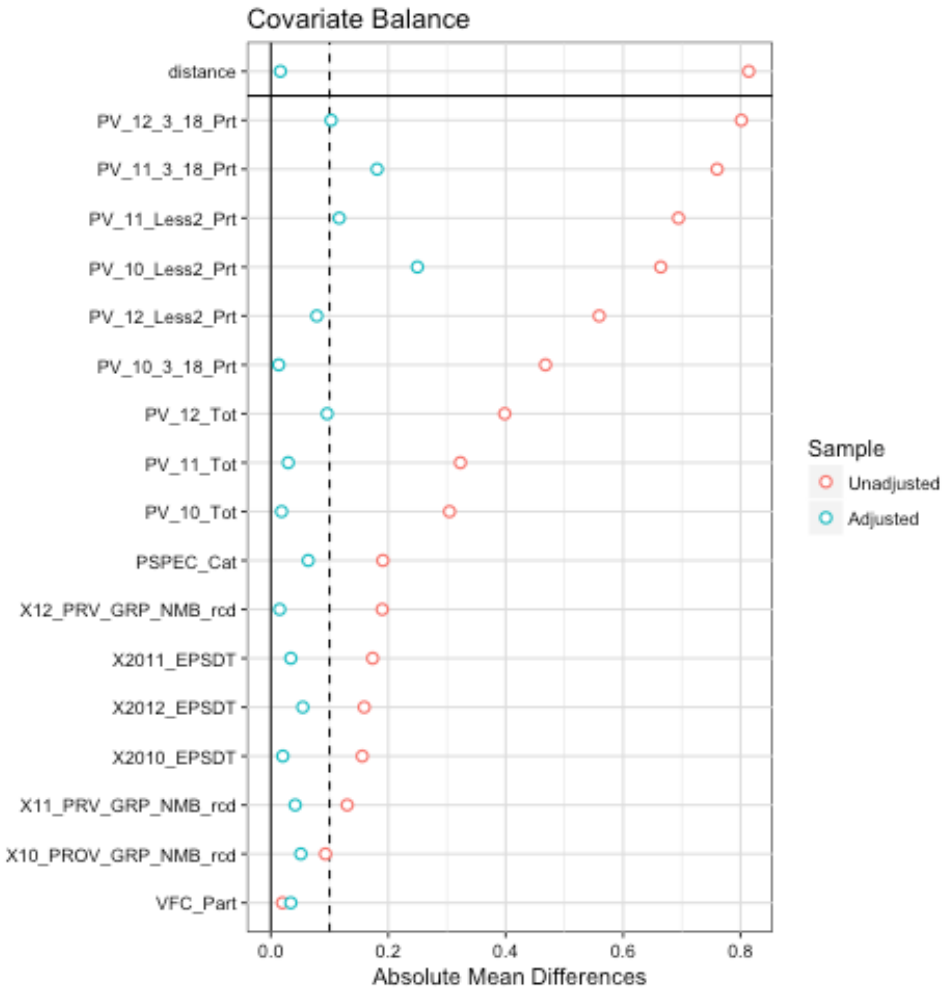


Figure 9: **Propensity Score Distribution, Nearest Neighbor, Without Replacement, No Record Discards**

Perhaps the best visualization of the impact of PSM on creating a suitable comparison group for analysis is a full-variable balance plot. The balance plot in Figure 10 shows each variable used in propensity score matching, pre- and post-matching. The dotted line is the 0.1 mean difference threshold. The closer each variable moves to the dotted line, the better the match.



Note: See Table 11 for variable details

Figure 10: Propensity Score Matching Balance Plot
The narrow spread of the Adjusted points compared with the broader spread of Unadjusted points indicates good balance.

Table 7 below shows the Welch T-Sample T-test, comparing the means of the matched intervention and comparison groups using the preferred 1:1 match ratio file. The large p-values denote that there is no statistically significant difference in means, comparing each intervention variable mean to its comparison group counterpart, supporting the contention the good balance suggested by Figure 10. The final variable list in Table 7, Propensity Score, is a product of the

PSM matching. The Propensity Score is the probability of each provider adopting an EHR in 2013 conditional on all other variables used in the PSM model; i.e. the mean propensity for both the intervention and comparison group to have an EHR given all covariates used in matching is 17 percent[9] (Adelson, 2013).

Table 7: Variables Used in Propensity Score Matching with 1:1 Match Ratio, Comparing Intervention to Comparison Group, Welch Two-Sample T-Test

Variable	Group Mean		CI (p-value)
	Intervention	Comparison	
Provider Specialty†	8.18	7.97	-0.97 – 0.45 (0.584)
VFC Participation*	0.35	0.39	-0.08 – 0.15 (0.548)
EPSDT Participation (CY)*			
2010	0.76	0.78	-0.76 – 0.12 (0.678)
2011	0.82	0.85	-0.05 – 0.12 (0.436)
2012	0.83	0.88	-0.03 – 0.13 (0.183)
Patient Volume (CY 2010)			
Total	4,203	4,092	-2,027– 1,804 (0.909)
% less than age 2	0.46	0.42	-0.09 – 0.002 (0.061)
% between ages 3 and 18	0.44	0.43	-0.05 – 0.04 (0.921)
Patient Volume (CY 2011)			
Total	4,248	4,415	-1,817 – 2,151 (0.869)
% less than age 2	0.44	0.42	-0.05 – 0.02 (0.358)
% between ages 3 and 18	0.47	0.51	-0.008 – 0.06 (0.150)
Patient Volume (CY 2012)			

[9] As stated above, "Match It" does not pair treatment with comparison, but instead minimizes the difference between the propensity of being in the treatment, comparing treatment to comparator, conditional on matching covariates.

Variable	Group Mean		CI (p-value)
	Intervention	Comparison	
Total	4,152	4,554	-1,574 – 2,379 (0.688)
% less than age 2	0.42	0.40	-0.05 – 0.02 (0.529)
% between ages 3 and 18	0.51	0.52	-0.12 – 0.05 (0.397)
Propensity Score	0.17	0.17	0.89

† "Provider Specialty" is a categorical variable.
* These variables are binary.

DATA ANALYSIS

This section provides the descriptive statistics of the data used in this analysis, details the model selection, and provides various analyses supporting the chosen model. The descriptive statistics show the minimum, maximum, mean, standard deviation and standard error for all variables used in the analysis, identified as either treatment, Potential Comparison (PC) group and Propensity Score Matching Comparison (PSMC) group. The model selection process uses the outcome data of interest – the number of children assigned to each primary care provider (PCP) who received the minimum number of vaccination does according to the Combination 7 (a "count" of the successes) – to specify either a Poisson or Negative Binomial model. Then, by evaluating prior distribution selections, a Chi-square-like calculation, posterior distributions, and other diagnostics, I analyze the impact of EHR use on vaccination rates.

With the match ratio defined, I have also defined the intervention and comparison groups, to whose descriptions I now turn.

DESCRIPTIVE STATISTICS

Table 8 below displays the descriptive statistics for the intervention (I), potential comparison group, pre-propensity score matching (PC), and the comparison group identified

post-propensity score matching (PSMC). The variables “Provider Specialty” and “Race” are categorical variables. The variables for Vaccine for Children Participation (“VFC Participation”), “State Payer EHR Incentive Program Participation”, “EHR Use” based on self-reported Board of Physicians data, and Early and Periodic Screening, Diagnostic, and Treatment participation (“EPSDT Participation”) are binary variables. “Immunization Status Score” is the HEDIS-like independent variable.

Table 8: **Descriptive Statistics, Intervention (I), Potential Comparison, (PC) and Propensity Score Matching Comparison Groups (PSMC)**

Variable	Min			Max			Mean			SD			SE		
	I	PC	PSMC	I	PC	PSMC	I	PC	PSMC	I	PC	PSMC	I	PC	PSMC
Provider Specialty¥	1	1	1	27	27	27	8.18	8.82	8.00	3.31	3.39	3.28	0.27	0.10	0.27
VFC Participation	0	0	0	1	1	1	0.35	0.33	0.39	0.48	0.47	0.49	0.04	0.01	0.04
EHR Use (%)															
2009	0	0	0	0	1	0	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00
2010	0	0	0	1	1	1	0.30	0.23	0.24	0.46	0.42	0.43	0.04	0.01	0.04
2011	0	0	0	1	1	1	0.32	0.22	0.17	0.47	0.41	0.38	0.04	0.01	0.03
2012	0	0	0	1	1	1	0.43	0.32	0.34	0.50	0.47	0.48	0.04	0.01	0.04
2013	0	0	0	1	1	1	0.34	0.26	0.18	0.48	0.44	0.39	0.04	0.01	0.03
State Payer EHR Incentive Program Participation (%)															
2011-2013	0	0	0	1	1	1	0.05	0.02	0.02	0.23	0.15	0.14	0.02	0.00	0.01
2014	0	0	0	1	1	1	0.12	0.03	0.04	0.32	0.17	0.20	0.03	0.00	0.02
EPSDT Participation (CY)*															
2010	0	0	0	1	1	1	0.76	0.61	0.78	0.43	0.49	0.41	0.04	0.01	0.03
2011	0	0	0	1	1	1	0.82	0.64	0.85	0.39	0.48	0.36	0.03	0.01	0.03
2012	0	0	0	1	1	1	0.83	0.67	0.88	0.38	0.47	0.32	0.03	0.01	0.03
2013	0	0	0	1	1	1	0.83	0.68	0.89	0.38	0.46	0.31	0.03	0.01	0.03
2014	0	0	0	1	1	1	0.83	0.69	0.90	0.38	0.46	0.30	0.03	0.01	0.03
Race	1	1	1	5	5	5	2.44	2.26	2.21	1.52	1.45	1.35	0.13	0.04	0.11
Patient Volume (CY 2010)															
Total	0	0	0	56,280	99,232	99,232	4,203	2,352	4,092	6,081	5,252	10,097	501.58	148.43	932.80
% < age 2	0	0	0	1.00	1.00	1.00	0.46	0.34	0.42	0.17	0.25	0.22	0.01	0.01	0.02

Variable	Min			Max			Mean			SD			SE		
	I	PC	PSMC	I	PC	PSMC	I	PC	PSMC	I	PC	PSMC	I	PC	PSMC
% between ages 3 and 18	0	0	0	0.78	1.00	1.00	0.44	0.36	0.43	0.16	0.22	0.21	0.01	0.01	0.02
Patient Volume (CY 2011)															
Total	58	0	0	48,305	109,079	109,079	4,247	2,430	4,415	5,629	5,480	10,832	464.27	154.87	893.46
% <age 2	0.12	0.00	0.00	0.77	1.00	0.73	0.44	0.35	0.42	0.13	0.24	0.16	0.01	0.01	0.01
% between ages 3 and 18	0.15	0.00	0.00	0.76	1.00	1.00	0.49	0.39	0.51	0.13	0.22	0.15	0.01	0.01	0.01
Patient Volume (CY 2012)															
Total	128	0	0	21,979	117,491	117,491	4,152	2,480	4,554	4,197	5,477	11,398	346.14	154.78	940.16
% < age 2	0.06	0.00	0.00	1.00	1.00	0.78	0.42	0.34	0.40	0.14	0.24	0.16	0.01	0.01	0.01
% between ages 3 and 18	0.00	0.00	0.00	0.87	1.00	1.00	0.51	0.39	0.52	0.15	0.22	0.15	0.01	0.01	0.01
Patient Volume (CY 2013)															
Total	2	0	0	35,494	81,373	81,373	4,188	2,167	3,850	5,028	4,484	8,807	414.66	126.72	726.36
% <age 2	0.00	0.00	0.00	1.00	1.00	0.85	0.41	0.31	0.40	0.16	0.24	0.19	0.01	0.01	0.02
% between ages 3 and 18	0.00	0.00	0.00	1.00	1.00	1.00	0.50	0.37	0.48	0.16	0.23	0.19	0.01	0.01	0.02
Patient Volume (CY 2014)															
Total	0	0	0	37,556	89,029	89,029	5,454	2,855	5,16	6,680	5,861	10,4997	550.92	165.64	907.00
% < age 2	0.00	0.00	0.00	0.98	1.00	1.00	0.39	0.29	0.38	0.17	0.24	0.21	0.01	0.01	0.02
% between ages 3 and 18	0.00	0.00	0.00	0.83	1.00	0.92	0.50	0.36	0.48	0.18	0.25	0.22	0.02	0.01	0.02
Immunization Status Score															
2010	0.00	0.00	0.00	1.00	1.00	1.00	0.17	0.12	0.16	0.24	0.23	0.23	0.02	0.01	0.02
2011	0.00	0.00	0.00	1.00	1.00	1.00	0.21	0.14	0.20	0.27	0.25	0.26	0.02	0.01	0.02
2012	0.00	0.00	0.00	1.00	1.00	1.00	0.20	0.17	0.22	0.23	0.27	0.28	0.02	0.01	0.02
2013	0.00	0.00	0.00	1.00	1.00	1.00	0.23	0.17	0.23	0.24	0.27	0.28	0.02	0.01	0.02
2014	0.00	0.00	0.00	1.00	1.00	1.00	0.24	0.18	0.23	0.22	0.26	0.23	0.02	0.01	0.02

Table 9 displays the results of a Welch two-sample t-test, comparing each of the yearly HEDIS® scores of the pre-PSM created comparison group (PC) and the post-PSM created comparison group (PSMC). Comparing the Intervention group to the Pre-PSM comparison group, there is a statistically significant difference in mean group HEDIS® score at the 0.05 significance level for the years 2010, 2011, 2013, and 2014. However, after PSM, there is no statistically significant difference in HEDIS® scores at the same significance level for any year.

Table 9: **HEDIS® Immunization Status Score by Year, Comparing the Intervention Group to Comparison Groups, Welch Two-Sample T-Test**

Calendar Year	Group Mean, HEDIS® Immunization Status Score (%)			CI (p-value)	
	I	PC	PSMC	I *vs.* PC	I *vs.* PSMC
2010	0.17	0.12	0.15	-0.09 – -0.01 (0.02)	-0.07 – 0.04 (0.63)
2011	0.21	0.14	0.19	-0.11 – -0.02 (<0.01)	-0.08 – 0.05 (0.63)
2012	0.20	0.17	0.23	-0.03 – 0.01 (0.12)	-0.03 – 0.09 (0.35)
2013	0.23	0.17	0.23	-0.11 – -0.02 (<0.01)	-0.06 – 0.06 (0.93)
2014	0.24	0.18	0.22	-0.10 – -0.03 (<0.01)	-0.08 – 0.03 (0.40)

SPECIFYING STATISTICAL APPROACH

The relationship between the data used for this analysis is complex, not only in it is collection (see Figure 7), but also due to its hierarchical structure. Figure 11 is a simplified visualization of the data's hierarchical nature. As Figure 11 shows, two providers (Level 2) may be affiliated with a single practice (Level 3) and be measured over two time periods (Level 1). In

practice, these relationships may be even more complex: over time, providers may move between primary groups[10], and thus have different group members.

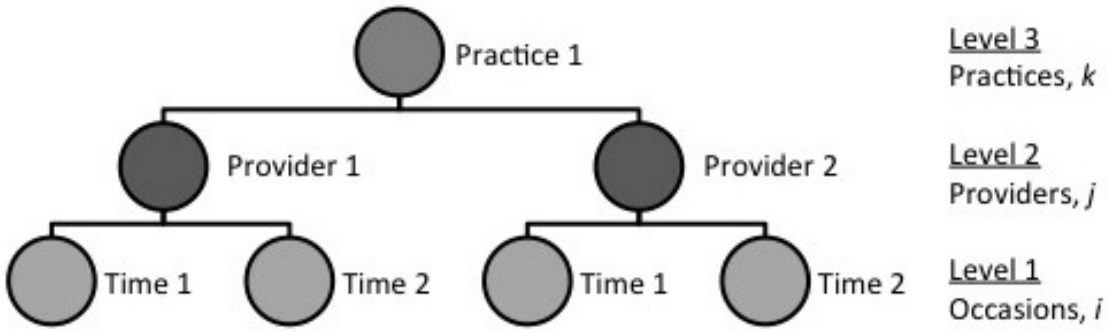


Figure 11: Depiction of Three-Level Design

There is also varying levels of uncertainty across each level of the data, with each level allowing for the integration of background information to inform the likelihood. For example, provider-level immunization rates are likely different than group-level immunization rates.

To address the many relationships between and the hierarchical nature of the data, I used a Bayesian-modeling method to address those relationships directly. This choice helps to address four concerns with modeling these data using a frequentist approach: (1) complexity of the relationships between the data; (2) the resulting uncertainty at each level of the data; (3) the relatively low sample size; and (4) the greater generalizability of the posterior distribution. According to Schoot and Depaoli, Bayesian statistics offer methodological benefits that address all four concerns (van de Schoot & Depaoli, 2014).

Because of this, a Bayesian approach can introduce prior distributions and current likelihood to model these differences.

[10] See *Group Affiliations*.

Furthermore, although this analysis uses many data points, the data is aggregated at the provider- and group-level, with the provider being the unit of analysis. This reduction process reduces the sample size to 294, a relatively small sample.

Finally, the Bayesian approach to evaluating posterior distributions allows me to report the probability that a mean estimate resides within an upper and lower bound (credible interval) for the sample population studied (van de Schoot & Depaoli, 2014).

TESTING MODEL SPECIFICATION

According to Sung et al. and van de Schoot and Depaoli, research using Bayesian statistics should present the following information: (1) the statistical program and sampling method, (2) the statistical model, (3) a discussion of prior distributions, and (4) any sensitivity analysis conducted, including a goodness-of-fit test (Johnson, 2004; Sung et al., 2005; van de Schoot & Depaoli, 2014).

Glickman and van Dyk (2007) break Bayesian analysis into four steps:

1. Formulate probability model that fits the data;
2. Determine *prior distributions*, which quantify uncertainty for unknown model parameters before the data are observed;
3. Using the data, determine the *likelihood function*. The likelihood function is combined with the prior distributions to determine the posterior distribution. Determining the posterior distribution quantifies uncertainty after the data is observed; and
4. Summarize features of the *posterior distribution* or calculate quantities of interest (Glickman & Dyk, 2007).

Before evaluating a model's outcomes, Bayesian analysis relies on software and parameters to specify the simulation. Each execution used in this analysis may have different parameters, such as iterations (or the number of times the model is run to generate posterior samples), thinning (the number of samples dropped per iteration), burn-in (the number of initial samples dropped to account for initial mixing of values), chains (the number of separate initial values that start an iteration), and adaptation (the initial values used before sampling that maximizes efficiency). When calling out or comparing models, I provide these parameters.

Upon arriving at step four of the Bayesian analysis process, I evaluated each model against each other model. The model evaluation process relied on two goodness-of-fit tests, a modified χ^2-like statistic and the Deviance Information Criterion (DIC). The modified χ^2-like goodness-of-fit test compares the proportion of posterior means exceeding the 95th quantile of a χ^2 distribution based on equally probable quantiles of a Poisson distribution derived at the base model's mean (Johnson, 2004). The DIC is a statistic used to compare models for their estimated expected discrepancy in predicting the same outcome with different data (Gelman, Andrew, Carlin, John B, Stern, Hal S., Rubin, 2004).

Formulation of Probability Model

To determine the appropriate statistical model, I considered the structure of the dependent variable. Because the primary objective of this analysis is to determine whether there is any difference in a provider's quality score, comparing providers who achieved meaningful use using a certified EHR and those who did not have an EHR, and because the model is hierarchical and longitudinal, the Bayesian model will account for random affects. Modeling for random effects

assumes that individual providers who may be a part of the same group using the same EHR will have his or her own approach to using the system and interacting with patients.

I now turn to details of the hierarchical model, the first step being the probabilistic distribution for the dependent variable. The dependent variable in this analysis is count data – the number of successful administrations of all required dosages of a vaccine under Immunization Status Score, Combination 7 for all patients attributed to a PCP within a calendar year. A major consideration for modeling count data is its dispersion (spread). For data that is over-dispersed, meaning the variance is greater than the mean, the negative binomial, instead of the more common Poisson distribution, is more frequently used (Ntzoufras, 2009).

As shown in Table 10, listing the variance versus mean for each measurement year shows variances many times the means, provided support for modeling these data using the negative binomial distribution. Additionally, an over-dispersion test using the change-point approach used in this analysis – summing the successes for years 2013 and 2014 – results in the same conclusion.

Table 10: Count of Successful Vaccine Administrations, Variance Versus Mean, by Year

Calendar Year	Vaccine Administration Counts		Variance/Mean
	Group Variance	Group Mean	
2010	93.27	4.34	21.49
2011	87.62	4.91	17.85
2012	141.67	6.32	22.42
2013	154.69	6.28	24.63
2014	109.25	5.73	19.07

Calendar Year	Vaccine Administration Counts		Variance/Mean
	Group Variance	Group Mean	
2013+2014	471.67	12.01	39.27

Note: All calculations are pre-PSM. Group mean for "2013 + 2014" post PSM is 9.28.

Although the negative binomial model may be more frequently used for over-dispersed data, other factors may be considered when choosing the appropriate model, particularly the distribution of posterior kernel density plots and how well the model predicts the count of successes compared to the number of actual successes. A posterior kernel density plot is a smoothed histogram displaying the estimates of the marginal conditional probably of sample results following an MCMC simulation (Alexander, Allen, & Bindoff, 2013; Ho et al., 2007). The iterative tuning process for formulating the model is specified in step three, determining the likelihood function.

I specified multiple models in an iterative fashion by first specifying the hypothesized model as a baseline, and then iteratively modifying the base model, using the DIC as the measure of merit. The hypothesized base model is a hierarchical, random effects, negative binomial model. I tested the impact of various groupings of covariates on the DIC. Then, taking the top four covariate combinations that produced the lowest DIC, I then modeled a Poisson versus negative binomial model, a non-hierarchical version of the model, a fixed- versus random-effects version, and the inclusion of a propensity score covariate[11] (see Appendix 3).

[11] Research on the necessity of adding to an analytic model the propensity score as a latent variable ("covariate adjustment") is mixed. McCandless, Gustafson, and Austin (2008) argue that researchers using propensity score analysis may model the uncertainty around a propensity score using Bayesian analysis (McCandless, Gustafson, & Austin, 2009). This approach would allow for propensity score covariate adjustment, or the inclusion the propensity score in the analytic model. Garrido (2016) discourages propensity score covariate adjustment, as it does not allow for balancing covariates, leads to inefficient estimates, among other things (Garrido, 2016). Because including the propensity score either improved or had no impact on the DIC across all model specifications, I included the propensity score as a latent variable.

Deciding on Prior Distribution

Prior distributions used throughout the model specification process are all non-informative conjugate priors. A non-informative conjugate prior is a higher-level prior distribution that is within the same family as the underlying distribution it is feeding within the model, but its distribution is specified to be vague (Glickman & Dyk, 2007).

Likelihood to Posterior Distribution

The likelihood function is derived by the equation (2), which states that the likelihood of *theta*, given *y* is the product of each of the probabilities of *y* given *theta*:

$$(2) \qquad L(\theta|y) = p(y_1, \ldots, y_n|\theta) = \prod_{i=1}^{n} p(y_i|\theta)$$

The posterior distribution of $p(\theta|y)$ is derived from Bayes' theorem or Bayes' rule, where the posterior distribution of *theta* given *y* is proportional to prior distribution of *theta* times the likelihood of *theta* given *y* (Glickman & Dyk, 2007). (equation 3):

$$(3) \qquad p(\theta|y) = \frac{p(\theta)p(\theta|y)}{\int p(\theta)p(y|\theta)d\theta} = \frac{p(\theta)L(\theta|y)}{p(y)} \propto p(\theta)L(\theta|y)$$

The calculation of the posterior distribution may be achieved through software. All models evaluated for this analysis are run using R (R Core Team, 2017). The package *rjags* (http://mcmc-jags.sourceforge.net) allows the user to build Bayesian analysis Using Gibbs Sampling (BUGS) models to run Markov Chain Monte Carlo (MCMC) simulations (Plummer,

2016). Gibbs sampling is a flavor of MCMC simulation that facilitates the "full conditional distributions of each unknown stochastic node conditional on the values of all other nodes" (Lunn, David, Spiegelhalter, David, Thomas, Andrew, Best, 2009). Its power is that it allows the analyst to articulate the desired model, without worrying about the behavior of test statistics associated with that model. To obtain desired outputs and to run diagnostics on MCMC samples, I used the Convergence Diagnosis and Output Analysis (CODA) package (Plummer, Martyn, Best, Nicky, Cowles, Kate, Vines, 2006).

Evaluating Posterior Results

To evaluate the various models, I visually inspected the sampling distributions for key nodes of the model to determine whether the samples are converging around a mean. For Bayesian models run using the CODA package, researchers can view posterior trace plots, which visualize the mean estimate for the node for each iteration and each chain. A chain is a posterior sample that begins from a different starting point than another chain. Researchers can also view kernel density plots, a smoothed histogram displaying the estimates of the marginal conditional probably of sample results following an MCMC simulation (Alexander et al., 2013; Ho et al., 2007). As shown in Figure 12, the key nodes observed include: the number of success expected (*r.expected*), the number of successes observed from the data (*r.observed*); and by provider and by EHR user (*p.provider*), the proportion of all patients affiliated to the provider who meet Immunization Status Score, Combination 7; and the primary outcome of interest, the change in Immunization Status Score due to EHR use (*delta.delta.mean.EHR*).

Next, I ran diagnostics on the quality of mixing and the presence of autocorrelation. Autocorrelation occurs when repeated observations are similar over certain periodicity. In

MCMC samples, autocorrelation can occur either within a sampling chain or between sampling chains. The Gelman and Rubin diagnostic statistic measures convergence in iterations and across chains by comparing within- and between-chain variances, with values close to 1 signaling good convergence (Martyn et al., 2016). I monitored autocorrelation, first using the Raftery and Lewis diagnostic and then generating autocorrelation diagrams. The Raftery and Lewis diagnostic calculates an "Independence Factor" for each variable within a chain. Values greater than 5 indicate autocorrelation (Martyn et al., 2016). No posterior estimates possessed an Independence Factor greater than 3.

Following the evaluative process outlined above, I identified two best-fit models, each are hierarchical, random effects models, with a Poisson distribution, and a propensity score covariate. One way to visualize a Bayesian model is to use a Directed Acyclic Graph (DAG). A DAG displays quantities represented by nodes, with each node linked to other nodes via arrows showing direct dependence (Lunn, David, Spiegelhalter, David, Thomas, Andrew, Best, 2009). Figure 12 is a DAG displaying a hierarchical logit model (comparing the HEDIS® score of EHR users to non-users) with a Poisson distribution at the provider (j,k) level. **The key parameter is *delta.delta.mean.EHR***, the change in, the change in immunization status score due to EHR use. The model incorporates fixed covariates for demographics, random effects at the provider (j) level, and data-derived group-mean data[12]. Prior distributions are all non-informative priors.

[12] Modeling fixed effects at the group level using the by-year, by-provider, group mean immunization status score assumes that there is a population group mean distribution impacting each group year modeled.

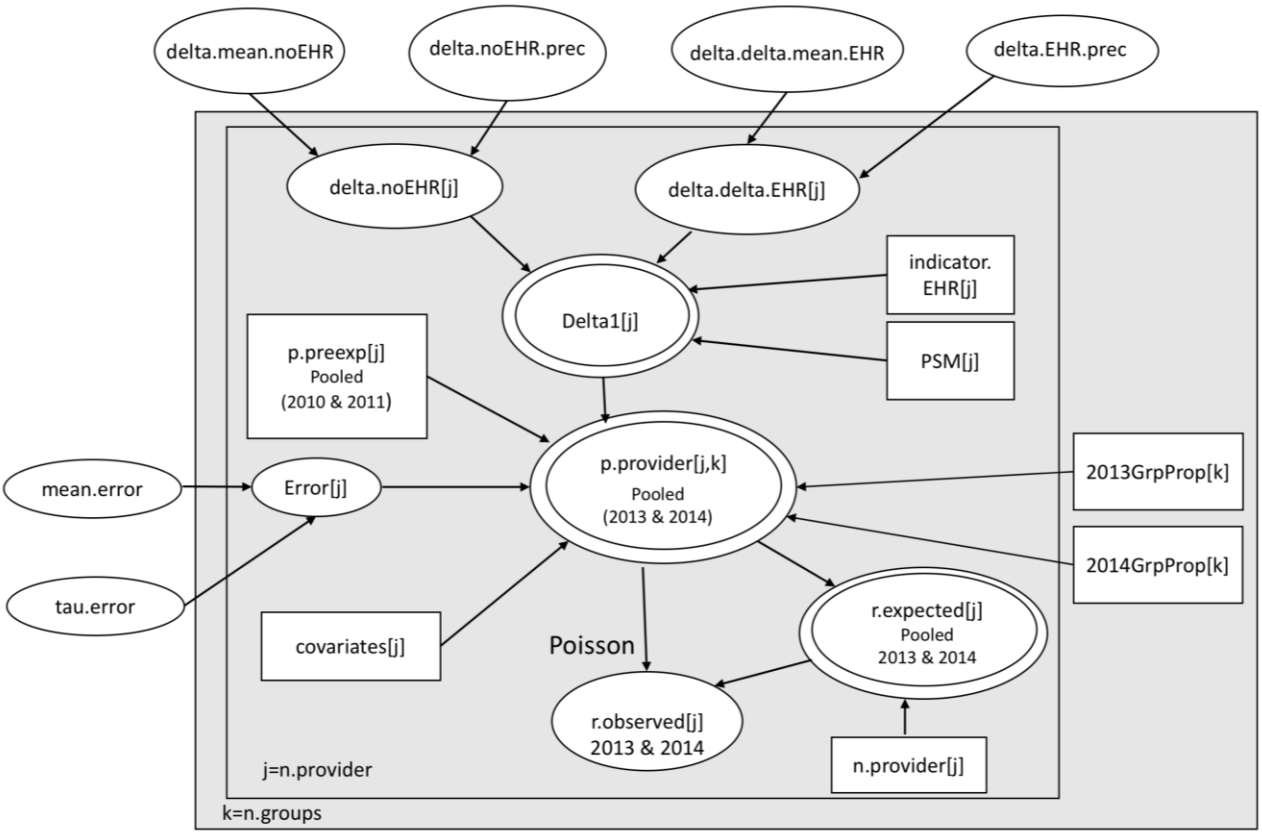


Figure 12: Directed Acyclic Graph for a Hierarchical Poisson Distribution for HEDIS® Scores, without Propensity Score Covariate Adjustment

Single ovals indicate stochastic nodes (variables with randomness and probability distributions), double ovals indicate deterministic nodes (variables dependent on parents), rectangles are deterministic nodes from the data. See Table 11 for explanations of the variable names.

In Figure 12, the hierarchical version of the logit model is specified at *p.provider[j,k]*. The logit model (with Poisson distribution) is fed by a series of data-derived constants (non-distributional covariates), stochastic nodes, and deterministic nodes. Stochastic nodes are variables with randomness and probability distributions. Deterministic nodes are variables dependent on either parent distributions or data. The details for each node are described in Table 11.

Table 11: List and Description of Nodes

Node	Description	Notes
Data-Derived Deterministic Nodes		
p.preexp[j]	The probability of successfully meeting Immunization Status Score Combo 7 pre-intervention (pooled years 2010 and 2011)	
covariates[j]	State Regulated Payor EHR Incentive Program participation, each of 2011-2013 and 2014 and licensure survey data for prior EHR use in years 2009 and 2010*	
2013GrpProp[k]	The total group Immunization Status Score Combo 7 group rate by group for 2013	
2014GrpProp[k]	The total group Immunization Status Score Combo 7 group rate by group for 2014	
n.provider[j]	The number of providers in the analysis (294)	
indicator.EHR[j]	A binary variable indicating whether provider is in the intervention group	
PSM[j]	Provider-specific propensity score	
Stochastic Nodes		
delta.noEHR[j]	The change in the probability of successfully meeting Immunization Status Score for non-EHR users	
delta.mean.noEHR	Population mean change in Immunization Status Score	Non-informative normal conjugate prior
delta.noEHR.prec	Variance of population mean change in Immunization Status Score	Non-informative gamma conjugate prior
delta.delta.EHR[j]	The change in the probability of successfully meeting Immunization Status Score, comparing EHR users to non-EHR users.	
delta.delta.mean.EHR	Population mean change in Immunization Status Score for EHR users	Non-informative normal conjugate prior
delta.EHR.prec	Variance of population mean change in Immunization Status Score for EHR users	Non-informative gamma conjugate prior
r.observed[j]	The observed number of successes (Immunization Status Score numerators)	Inferred by p.provider, but fed directly from r.expected[j] as a Poisson distribution

Node	Description	Notes
Error[j]	Provider-level random-effects	
mean.error	Population-level random effects	Non-informative normal conjugate prior
tau.error	Population-level random effects variance	Non-informative gamma conjugate prior
Deterministic Nodes		
Delta1[j]§	The primary node estimating the change in the probability of successfully meeting Immunization Status score. *Delta1[j] = delta.delta.EHR[j]*indicator.EHR[j] + delta.noEHR[j]+PSM[j]*	
p.provider[j,k]	The success rate for provider [j] in group [k].	
r.expected[j]	The expected number of successes for provider [j].	

* As stated in the Study Design section, the author removed calendar year 2012 from the analysis to account for various unknown time periods in which EHR Incentive Program participants may have installed their EHRs. See Figure 4.

§ *Delta1[j] = delta.noEHR + PSM* for non-EHR users; *Delta1[j] = delta.delta.EHR[j] + delta.noEHR + PSM* for EHR users.

As stated above, sensitivity analysis during model specification centered around the model primary distribution (negative binomial versus Poisson), addition of covariates, and the number of iterations. I chose the primary model parameters based on posterior trace, kernel density plots, and DIC, with more evidence supporting a Poisson distribution than negative binomial. The DIC is a statistic used to compare models for their estimated expected discrepancy in predicting the same outcome with different data (Gelman, Andrew, Carlin, John B, Stern, Hal S., Rubin, 2004).

Following the above process, I narrowed the models to four Poisson distribution models, both executed with 1,000 adaptations, 20,000 iterations, 4 chains, 1,000 burn-in. This means that

final posterior distributions are evaluated at 20,000 samples in each of 4 chains (adaptions and burn-in are accounted for before initializing iterations).

To compare models, I used a modified χ^2-like goodness-of-fit test (A. Gelman et al., 1996; Johnson, 2004). A tradition χ^2-statistic compares the sum of squares of standardized residuals for the expected values under a particular model (Gelman et al., 1996). A weakness in Gelman's approach to developing a χ^2-like statistic is that it does not have a χ^2 distribution. Having a χ^2 distribution facilitates model comparison through *p*-values (Johnson, 2004). One component of Johnson's χ^2-like goodness-of-fit test compares the proportion of posterior means exceeding the 95th quantile of a χ^2_9 distribution based on equally probable quantiles of a Poisson distribution derived at the base model's mean.[13]

Table 12 compares the top two Poisson models goodness-of-fit as evaluated by the posterior mean samples of the expected number of successful Immunization Status Combination 7 Scores and the DIC. Column 3 of Table 12 shows that the posterior distribution for the odds of successfully meeting Immunization Status scores is slightly better for the model containing both State Regulated Payor Incentive Program and EPSDT participation. However, the model containing only State Regulated Payor Incentive Program participation generates a lower DIC. Due to the strength of the chi-square-like statistic's ability to detect nonconformance of the evaluated model against a base model using the modeled data's mean, I chose to report results using Model 2, below.

[13] According to Johnson, bin quantiles used for the K-1 χ^2 degrees of freedom calculations may be calculated as the sample size raised to the 0.4 (294^0.4 = 9.7, rounded to 10).

Table 12: Goodness-of-Fit Comparison Statistics

Model	Covariates	Proportion of Posterior Sampled Means >16.9	DIC
1	State EHR Incentive Program Participation	0.169	1119
2	State EHR Incentive Program Participation and EPSDT Participation	0.165	1123

Note 1: Column 3 compares the proportion of mean samples exceeding the χ^2 distribution with 9 degrees of freedom at 0.05 significance level.
Note 2: A lower value DIC is evidence that the model is a better fit of the data.

Chapter 4
Results

This study investigates the effect of adopting an EHR and meeting the Meaningful Use criteria Clinical Quality Measure (eCQM) NQF 0038 "Childhood Immunization Status", on HEDIS®-based quality metric, Childhood Immunization Status (CIS) Combination 7, comparing EHR users to non-users pre-and post-implementation of the EHR Incentive Program in Maryland Medicaid. To estimate this effect, I modeled a Poisson distribution, creating the node *Delta1[j]*. The covariate *delta.delta.EHR[j]* estimates the change in the log-odds of meeting CIS for each provider, comparing EHR users to non-users. This formula is shown in Equation (4).

$$Delta1[j] = delta.delta.EHR[j] * EHR.indicator + delta.noEHR[j] + PSM[j] \quad (4)$$

Bayesian analysis allows me to calculate the mean change in the change in CIS due to EHR use, as specified in *delta.delta.mean.EHR* (see the stochastic, population-level node feeding delta.delta.EHR[j] in Figure 12). *delta.delta.mean.EHR* is used to calculate the posterior population estimated mean for the log-odds change in CIS due to EHR use. Figure 13 shows the posterior sampling distribution for the mean change in the log-odds change in CIS due to EHR use. Each color of the trace plot represents a chain in the simulation that begins at a unique initial starting point. The graphic shows good mixing across the sampled posterior values across chains,

centering around a mean of 0.20 (log-odds of 0.20). The kernel density plot – or smoothed frequency graph – shows the same mean, 0.20.

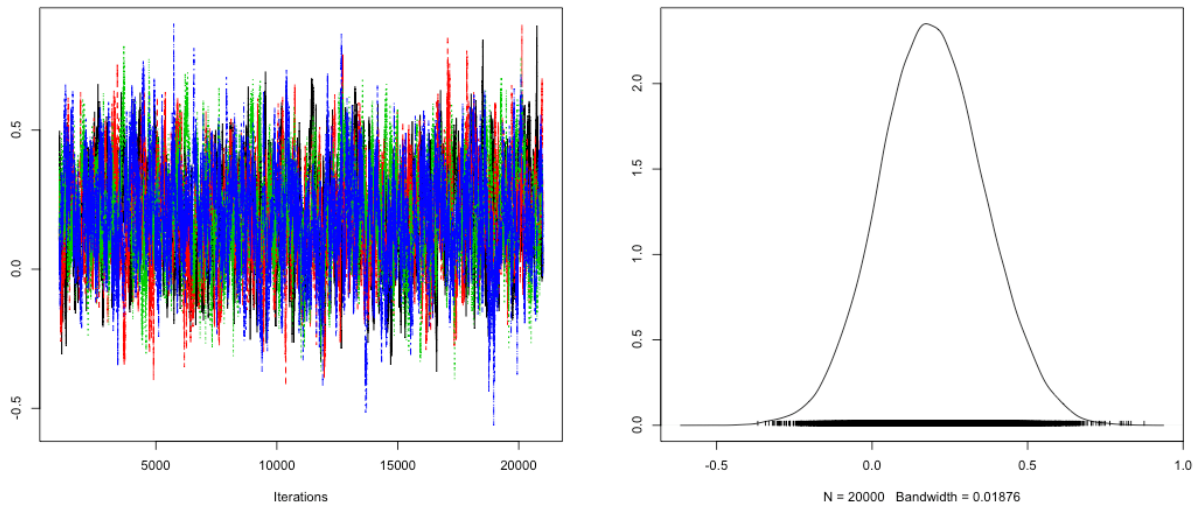


Figure 13. Trace and Kernel Density Plot of the Log-Odds of the Mean Change in the Change in CIS Due to EHR Use

By exponentiating the mean posterior value of 0.20 estimated and displayed in Figure 13, I can report results as the estimated improvement in the odds of improving CIS due to EHR use. Table 13 shows the mean and credible interval for the exponentiated estimates from Figure 13.

Table 13. Mean Change in the Change in Odds of Increasing CIS Score Due to EHR Use

Variable	Mean	SD	95% Credible Set
delta.delta.mean.EHR	1.21	4.50	(0.88 – 1.73)

Note: All values transform posterior sample results obtained from Figure 13.

Given prior information for and probabilities obtained from the data used in this study, I estimate that for providers using EHR's in this study, their use of the EHR increased the odds of meeting immunization status score requirements for providers by an average of 21 percent.

However, if the credible set of the odds contains 1, then EHR use may not increase the odds of meeting CIS score criteria for providers. Because the 95 percent credible set does contain 1, the percent improvement in odds is not significant.

Thus, based on prior information and the probabilities calculated with this data set, for Maryland Medicaid MCO network providers, in the two-year, post-EHR implementation period (the "intervention"), there is no statistically significant difference in the percent change in CIS Combination 7 score, comparing providers meeting Meaningful Use with Clinical Quality Measure (eCQM) National Quality Forum 0038 "Childhood Immunization Status," to non-EHR users.

A secondary aim of this study is to better understand whether the change in provider quality score differs by EHR developer. This question may be particularly important to answer given the large standard deviation shown in the estimated increase in the mean odds of meeting CIS criteria.

To evaluate the correlation between a particular EHR developer and a provider's probability of successfully meeting Childhood Immunization Status (CIS) Combination 7, I re-specified the model at Figure 12 to break the overall EHR-use delta into seven interaction terms, one for each of the six EHR developers with at least 10 users, and a seventh interaction term for all other EHR users. As is detailed above, each vendor-specific *delta.delta* interaction term is fed by a population-based mean. This re-specification results in equation (5). Equation (5) allows me to estimate the mean change in the change in the odds of meeting EHR immunization status score by EHR developer.

(5) $$Delta1[j] = delta.delta.EHRvendor1[j] * EHR.indicator * EHRvendor1[j] + delta.delta.EHRvendor2[j] * EHR.indicator * EHRvendor2[j] \ldots + delta.noEHR[j] + PSM[j]$$

Note: The ellipses denote continue iteration of the equation interact terms, each for EHR vendors 3 through 6, and a seventh interact term for all other EHR vendors.

To estimate whether the change in the odds is statistically significantly different than the overall EHR-use posterior estimate from Table 13, I performed a Welch two-sample t-test for unequal variances, comparing each EHR-developer specific posterior population mean estimate to the overall intervention estimated mean change in probability of meeting CIS Combination 7.

Table 14 lists only those EHR developers with ten or more users and the group mean change in HEDIS® scores. Only those estimates with credible sets not containing 1 are denoted with an asterisk. Only Epic produced a credible set that did not contain 1, when comparing the group mean change in immunization score to that of the overall intervention group mean.

Table 14: Effect of EHR Developer on Immunization Status Score

EHR Developer	Number of Users	Absolute Difference in Odds of Meeting CIS, Comparing EHR Developer to All EHR Users
Allscripts	13	-0.34
Aprima Medical Software, Inc.	10	0.02
eClinicalWorks, LLC	38	0.87
Epic Systems Corporation	16	-0.88*

EHR Developer	Number of Users	Absolute Difference in Odds of Meeting CIS, Comparing EHR Developer to All EHR Users
GE Healthcare	17	0.59
Sage	10	0.43

Note 1: Welch, two-sample t-test, comparing EHR developer user change in group mean odds to EHR developer overall change in mean odds (1.21).

Note 2: EHR vendors with group membership less than 10: Acrendo Software, Inc., Amazing Charts, athenahealth, Inc., Bizmatics, Inc., Connexin Software, Inc., drchrono, Inc, Enable healthcare, Inc., Glenwood Systems, LLC., Greenway Health, LLC, MedPlus, Practice Fusion, and Viteria Healthcare Solutions, LLC.

* Credible Sets not containing 1.

In sum, comparing EHR users meeting Meaningful Use and successfully meeting Clinical Quality Measure (eCQM) National Quality Forum 0038 "Childhood Immunization Status" in Calendar Year 2013 (the "treatment" group) to a propensity-score matched provider population not adopting an EHR (the "comparison" group) two-years each during pre- and post-implementation, revealed no statistically significant difference in the odds of meeting Childhood Immunization Status (CIS) Combination 7. Further, only one EHR developer's product showed a statistically significant negative difference in the probability of meeting Childhood Immunization Status (CIS) Combination 7, compared to the overall group intervention mean.

Chapter 5
Discussion and Policy Implications

CONCLUSION

This study contributes to the small but growing literature on the effects of EHR use on health care quality by focusing specifically on the Medicaid managed care population. I constructed a quality outcome measure by applying a version of the HEDIS® specifications for Childhood Immunization Status (CIS), Combination Measure 7 to the individual provider and not Managed Care Organization (MCO) level, as is traditionally done. To apply the CIS Combination 7 measure to the provider level, I queried the Medicaid health care encounter file to identify the earliest Evaluation and Management (E&M), preventative medicine CPT code, to act as a binding agent between a patient and a provider. Once I identified the group of patients for whom the provider would be responsible for, I totaled the number of patients receiving the specified type and number of immunizations.

Using a Bayesian hierarchical model, I found no statistically significant difference in the change in the odds of meeting Childhood Immunization Status (CIS) Combination 7, comparing certain EHR users to a propensity-score matched group of EHR non-users. Additionally, among those providers who did adopt an EHR, comparing provider group means by EHR developer to the overall EHR user group mean, only one EHR developer product produced a statistically significantly change in the probability of meeting Childhood Immunization Status (CIS)

Combination 7. However, this change in odds is a decrease in the odds of meeting CIS Combination 7, compared to the overall difference in odds of meeting CIS due to EHR use.

DISCUSSION AND POLICY IMPLICATIONS

Nearly seven years after the start of the Medicaid EHR Incentive Program, researchers, providers, and policymakers have voiced their opinions about how the EHR Incentive Program has impacted providers and patients. For researchers, the creation of EHR certification has created more standardized EHR products, which has helped researchers to isolate EHR functionality. But, this rigidity in EHR product functionality for certification creates barriers to use among certain health care provider populations and settings, particularly solo practitioners, specialists, and rural providers (Heisey-Grove, Danehy, Consolazio, Lynch, & Mostashari, 2014). As a response to these concerns, as well as a response to the uncertainty around the link between Meaningful Use measures and improved care, the Centers for Medicare and Medicaid Services (CMS) is exploring how to change "Meaningful Use" to "Meaningful Measures" (CMS, 2018).

Despite the change in policy focus from mandating certain functions and reporting to more outcomes-based measures and value-based payments, the digitization of the health record remains and will likely play a large role in the future of health care. All major national policies around value-based, instead of fee-for-service-based, payments either include requirements that health care providers use CEHRT or are incentivized to do so.[14] This means that over time, as more providers adopt CEHRT, the level, fidelity, and timeliness of clinical data's availability to

[14] See the requirements for participation for the Quality Payment Program (QPP) at https://qpp.cms.gov/mips/advancing-care-information and demonstrations under the Innovation Center at https://innovation.cms.gov/initiatives/index.html#views=models.

the three major stakeholders in the health system (see Figure 1) will only improve. For Medicaid agencies particularly, as they continue to leverage federal funding to modernize their Medicaid Management Information Systems (MMIS), Medicaid agencies will be integrating clinical data with administrative data to measure quality. In this future state, Medicaid agencies will likely use quality scores as calls-to-action, revealing trends in patient health status to providers and Managed Care Organizations as a means to target interventions to improve quality for the individual *before* health declines, instead of using quality scores as a posterior, population-based summary statistic.

However, for immunization status reporting particularly, it does not appear as though EHR use has a differential impact on immunization rates. This study design does not provide information on particular EHR implementation approaches or whether EHR use improves immunization status (as measured by over- or under-immunization rates), thus I cannot conclude whether policies that continue to incent or require EHR use are beneficial for immunization status rates. Since many providers have already adopted EHRs, providers should begin to fully utilize their EHRs by imbedding them into their work flow and leveraging functionality to drive clinical performance. This research highlights that, although providers may choose to be measured on a particular quality metric due to their specialization and patient population, just because they have adopted an EHR does not mean that that EHR will improve their score or that the EHR is meant to improve that particular measure's score.

Further, due to the relatively short post-implementation timeline, I can neither confirm nor deny the presence of a "ramp-up" period for fully utilizing an EHR, as hypothesized by Cheriff, Kapur, Qui, and Cole (2010). There is some level of evidence to support the theory that, even though a provider chooses to be measured against a specific quality outcome such as

immunization rates, the initial two-years of using an EHR may decrease the odds of meeting immunization status scores. Why this may be the case and how far-reaching the impact is cannot be concluded using this study.

Because there is some evidence to support the theory that the impact of EHR use on immunization status score vary by EHR developer, the developer that a provider chooses should play a key role in the provider's ability to deliver quality care. Unfortunately, just at a time when CEHRT has made it easier for providers to select technology with certain baseline functionality, it has also made it difficult for providers to obtain EHRs that are tailored to their needs, which is where EHR use will actually be more meaningful (Payne et al., 2015). And, because of the high transition costs to move to another EHR platform, providers may be less likely to switch to a more tailored EHR (ONC, 2105). By reducing information blocking by vendors and other provider group and reducing the regulatory requirements for CEHRT, providers may be more likely to obtain either new EHRs or software that is a compatible add-on to their current EHR systems that can help them optimize quality scores and eventually patient outcomes.

STRENGTHS AND LIMITATIONS

Some of the major strengths of this study are found in the design and in the selection of outcome measures. This research uses an interrupted time series design that retrospectively follows particular providers and comparators over time. The use of a Bayesian hierarchical model accounts for correlation between providers and their practices. The study design creates a "contamination buffer" which allows for various implementation timelines for providers adopting an EHR. This research uses a constant, reliable, and valid outcome measure (HEDIS®

scores), and uses a retrospective approach to obtain data that has already been collected. The data collection is routine and is generally calculated using claims data supplied by MCOs.

Reporting results using Bayesian analysis is in contrast to the frequentist approach, which can only report confidence intervals in relation to replications of the exact same experiment (van de Schoot & Depaoli, 2014). The former approach is preferable in this analysis, as I would like to present results as impacting the population and not simply the population within the same experiment. Additionally, Bayesian analysis allows me to model uncertainty, which may arise around unmeasured motivational confounders, such as other programs that overtly or covertly incentivized EHR use.

The analytic model uses propensity score matching to create the comparison groups and a Medicare-approved patient attribution method to link patients and providers. The high match rate score for the comparison population reduces the likelihood of selection and unmeasured confounding bias, providing confidence in the estimated treatment effect (EHR use) on the outcome of interest (odds of meeting immunization status requirements). Additionally, the Medicare-approved patient attribution method provides support that provider-based immunization status rates are a good measures of a provider's patient cohort's immunization status.

Due in part to the nested nature of the study, the introduction of each layer adds more "noise" to the model. To mitigate the noise, this research could have analyzed HEDIS® scores at the practice level; however, such an analysis would not address the impact of EHR use on a provider's ability to improve health care quality, which is the primary research question. The Bayesian approach allows me to explicitly model these errors using error probability

distributions (via random effects), thus mitigating the impact of uncertainty at each level while allowing me to answer the primary research question.

As with all studies that utilize PSM to develop comparison groups, this study assumes non-ignorability or selection on observables to define covariates for propensity score matching. I tried to mitigate this weakness by using data supported by immunization research.

A weakness of this study is that I only had two years of data post implementation. This study compares data two years before and two years after implementation of the Medicaid EHR Incentive Program and expects to see a noticeable change in quality after EHR implementation within one year. Although it is reasonable to assume that a change in HEDIS® scores may occur within a year, it may not be accurate to assume that every provider who self-selected as implementing an EHR in 2013 did so at the same time and at the same level. It is possible that EHR implementation may take different providers different amounts of time and that, once implemented, different providers may take longer to fully integrate the system into their practice workflow. However, it would be difficult to know when exactly a provider fully implemented an EHR system; and, to make controls comparable, it would be difficult to obtain comparable quality measures at set intervals for every provider.

An additional weakness in this study is the assumption that a provider's primary group is the group from which a majority of their claims and encounters derive or, if this number remains equal across all groups, the amount of time spent with a group over the lifetime of the provider's enrollment with Medicaid. This assumption is plausible, as claim volume attributed to and time spent with a group likely stand for a proxy for the amount of physical time spent delivering care at the particular practice.

Another limitation of this study is the assumption that Medicaid recipients are similar across the providers that see them. Some studies attempt to mitigate this risk by adding a case-mix variable that accounts for the disease severity of the individual recipient. In this study, I assume that the independent variable of interest (meeting Meaningful Use) is independent of the disease severity of a provider's patient population and the provider's decision to acquire an EHR.

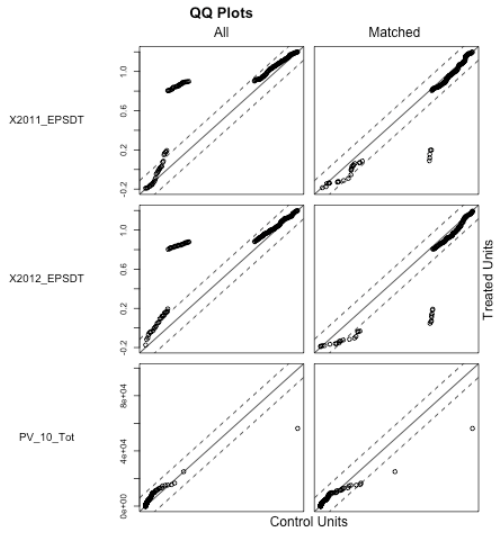
Lastly, I did not control for particular group and provider characteristics such as how a group implemented their EHR, how an individual provider used the EHR, and whether or not providers are aware of the immunization schedule and will administer vaccines according to the schedule. "Implementation" includes training as well as the activation of non-CEHRT-required functionality, such as alerts, which may differentially impact how a provider delivers care. These group- and provider-level characteristics may introduce bias.

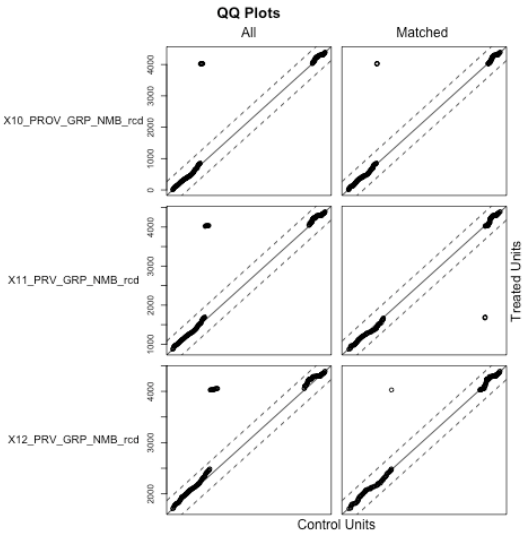
FUTURE RESEARCH

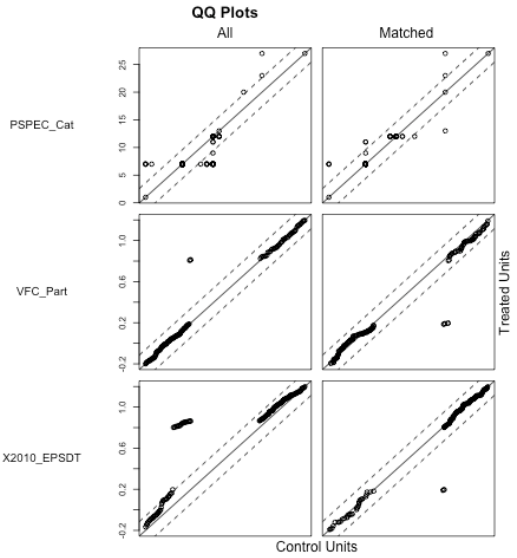
Additional areas of research resulting from this study include: (1) the investigation of individual EHRs that showed a statistically significant difference in the probability of meeting Childhood Immunization Status (CIS) Combination 7 to determine whether they provided additional functionality that impacted immunization rates; (2) quantifying the extent to which using an EHR impacted the over- or under-immunization of children empaneled to their Primary Care Provider; and (3) using the clinical information contained within an EHR to calculate the same CIS score and comparing it to claims and encounter data to determine whether EHRs more accurately capture immunization status.

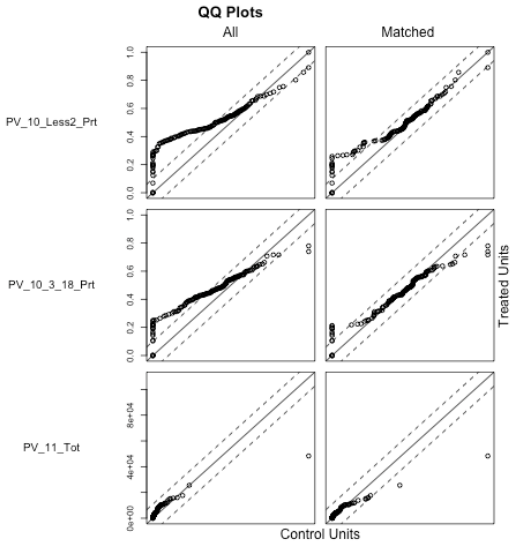
Appendix 1

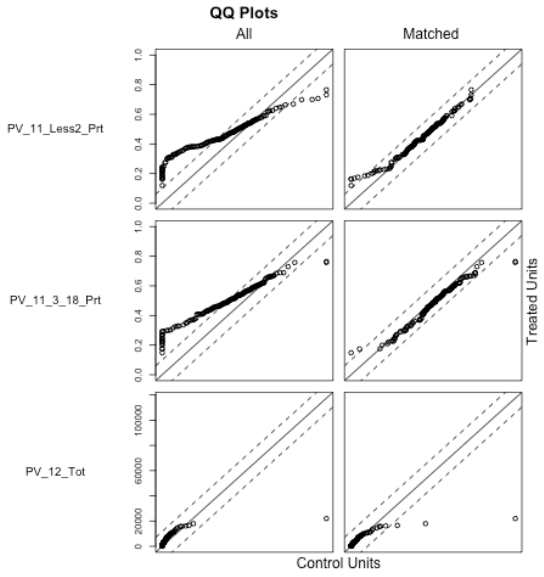
QQ Plots for 1:1 Nearest Neighbor Propensity Score Matching

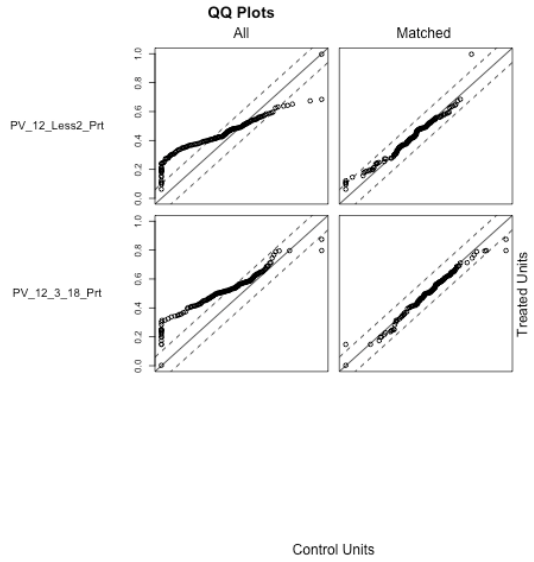












List of variables and their description

PSPEC_Cat: Health care provider specialty.

PV_10_Tot: Health care provider total claims and encounters for CY 2010.

PV_10_Less2_Prt: Health care provider percent of total claims and encounters for children <=2 on date of service, CY 2010.

PV_10_3_18_Prt: Health care provider percent of total claims and encounters for children <=18 and >=3 on date of service, CY 2010.

PV_11_Tot: Health care provider total claims and encounters for CY 2011.

PV_11_Less2_Prt: Health care provider percent of total claims and encounters for children <=2 on date of service, CY 2011.

PV_11_3_18_Prt Health care provider percent of total claims and encounters for children <=18 and >=3 on date of service, CY 2011.

PV_12_Tot: Health care provider total claims and encounters for CY 2012.

PV_12_Less2_Prt: Health care provider percent of total claims and encounters for children <=2 on date of service, CY 2012.

PV_12_3_18_Prt Health care provider percent of total claims and encounters for children <=18 and >=3 on date of service, CY 2012.

VFC_Part: Dichotomous variable for ever-participation in the Vaccines for Children Program.

X10_PROV_GRP_NMB_rcd: Predominate group affiliation, CY2010.

X11_PRV_GRP_NMB_rcd: Predominate group affiliation, CY2011.

X12_PRV_GRP_NMB_rcd: Predominate group affiliation, CY2012.

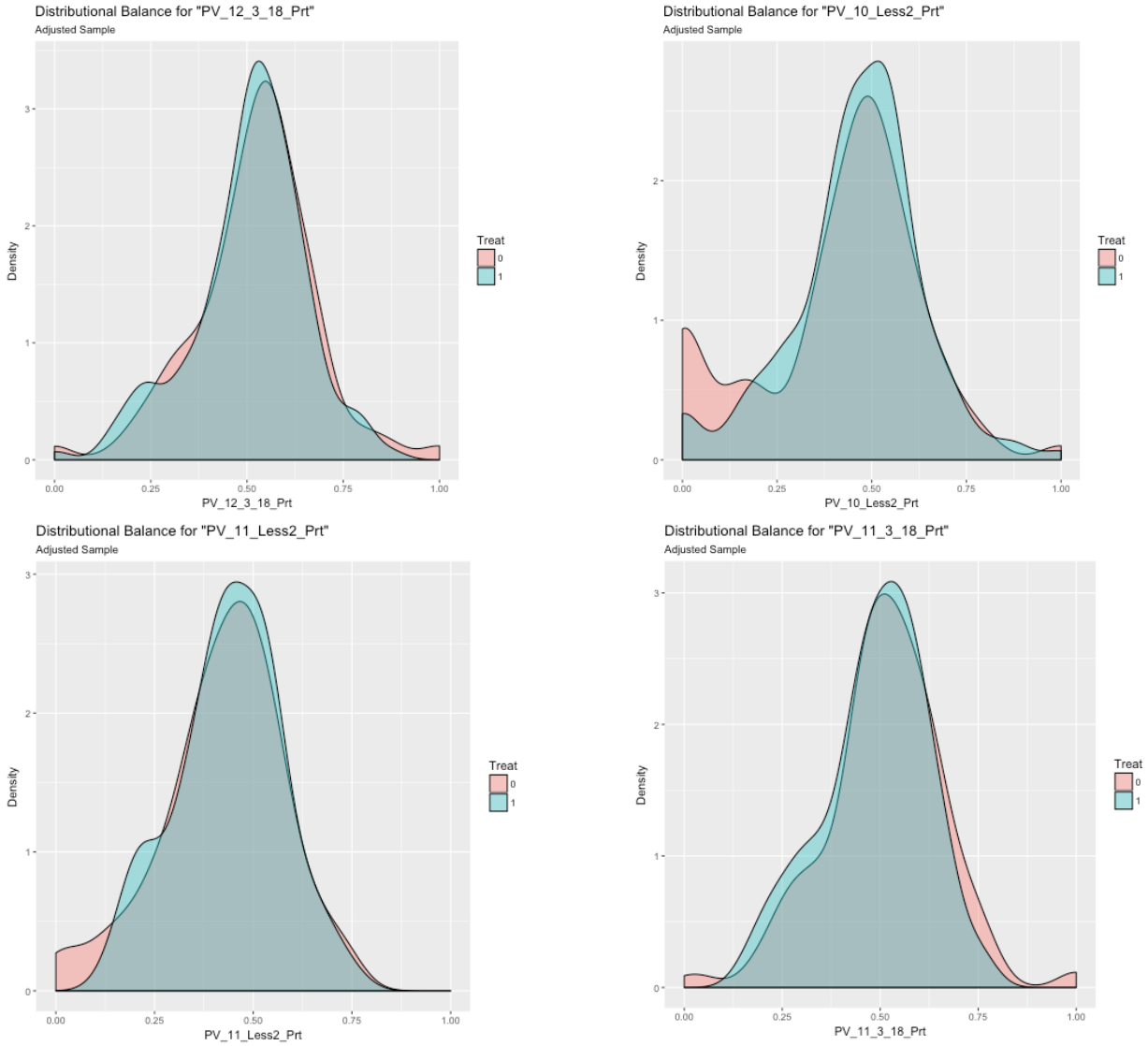
X2010_EPSDT: Participation in the Early Periodic Screening and Diagnosis Program, CY 2010.

X2011_EPSDT: Participation in the Early Periodic Screening and Diagnosis Program, CY 2011.

X2012_EPSDT: Participation in the Early Periodic Screening and Diagnosis Program, CY 2012.

Appendix 2

Propensity Score Matching Balance Table for Top-Three Least-Balanced Covariates



At a 0.1 mean difference threshold, *PV_10_Less2_Prt*, *PV_11_Less2_Prt*, and *PV_11_3_18_Prt*, exceeded the threshold. Variable *PV_12_3_18_Prt* balance plot provided for comparison.

Appendix 3

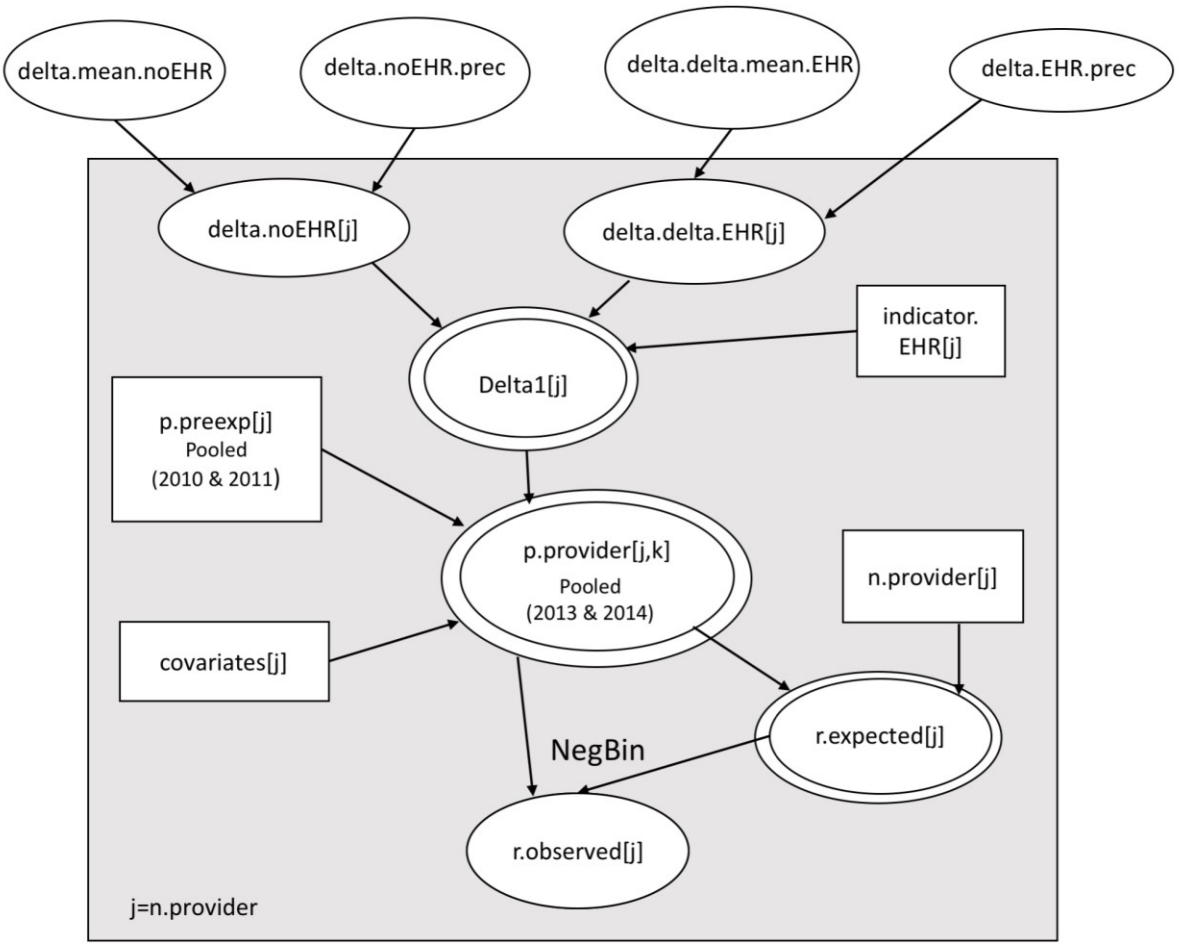
Select Models Evaluated using DIC as Figure of Merit

Model No.	Level		Specification		Distribution		PSM as Covariate
	Hierarchical	Non-Hierarchical	Fixed Effects	Random Effects	Poisson	Negative Binomial*	
1	1120	1122	1120	1120	1120	1610	1119
2	1123	1125	1123	1123	1123	1674	1123
3	1125	1126	1125	1126	1125	1768	1125
4	1125	1127	1125	1127	1125	1839	1125

Note 1: For each model number, the covariate package changes. Each covariate package is applied to a different model parameter in sequence, first by level, then specification, then distribution. The best version of the "level" model, is then tested against each type of "specification." The best "level" and "specification" pair is tested against each "distribution." Last, the propensity score is added as a covariate.

Note 2:
Model No. 1 covariates = State EHR Incentive Program Participation
Model No. 2 covariates = State EHR Incentive Program Participation and EPSDT Participation
Model No. 3 covariates = EPSDT Participation
Model No. 4 covariates = State EHR Incentive Program Participation and Past EHR Use (State licensure survey)

*DIC is the penalized DIC; all Poisson models were not penalized.
** Low numbers are better.



Directed Acyclic Graph for a Non-Hierarchical Negative Binomial Distribution for HEDIS® Scores, with Fixed Effects.

Single ovals indicate stochastic nodes (variables with randomness and probability distributions), double ovals indicate deterministic nodes (variables dependent on parents), rectangles are deterministic nodes from the data….See Table 11 for explanations of the variable names.

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